CHAPTER 2

HOW TO ADDRESS THE SYSTEMIC PART OF LIQUIDITY RISK

Summary

The financial crisis highlighted the lack of sound liquidity risk management at financial institutions and the need to address systemic liquidity risk—the risk that multiple institutions may face simultaneous difficulties in rolling over their short-term debts or in obtaining new short-term funding through widespread dislocations of money and capital markets. Under Basel III, individual banks will have to maintain higher and better-quality liquid assets and to better manage their liquidity risk. However, because they target only individual banks, the Basel III liquidity rules can play only a limited role in addressing systemic liquidity risk concerns. Larger liquidity buffers at each bank should lower the risk that multiple institutions will simultaneously face liquidity shortfalls; but the Basel III rules do not address the additional risk of such simultaneous shortfalls arising out of the interconnectedness of various institutions across a host of financial markets. More needs to be done to develop macroprudential techniques to measure and mitigate systemic liquidity risks.

The chapter suggests three separate methods of measuring systemic liquidity risk, each of which could be used to construct a macroprudential tool. Each technique measures an institution's ongoing contribution to systemwide liquidity risk, thereby establishing an objective basis on which to charge an institution for the externality it imposes on the financial system. The details of the methods described here are only illustrative. Moreover, it is unrealistic to expect there to be a single, best measure for systemic liquidity risk, so the three measures should be viewed as complementary.

The chapter does not take a view on the type of charge that would be best for mitigating systemic liquidity risk—a macroprudential capital surcharge, fee, tax, insurance premium, or some other instrument. Rather, it stresses the importance of having a macroprudential tool that would allow for a more effective private-public burden sharing of systemic liquidity risk management, which in turn would help minimize the tendency for financial institutions to collectively underprice liquidity risk in good times.

The approach taken to address systemic liquidity risk should be multipronged and build on the recommendations made in the October 2010 GFSR, which noted that improvements in market infrastructure could help mitigate systemic liquidity risks. For instance, some risks associated with collateral management in secured funding markets could be addressed through greater use of central counterparties for repurchase agreements and through-the-cycle haircuts, or minimum haircut requirements, for collateral. Also, nonbank financial institutions that contribute to systemic liquidity risk should receive more oversight and regulation. Many of these recommendations are still being implemented.

Policymakers will need to be conscious of the interactive effects of multiple approaches to mitigate systemic risks. For instance, add-on capital surcharges or other tools to control systemic solvency risk could also help lower systemic liquidity risk, allowing less reliance on mitigation techniques that directly address liquidity. Finally, more needs to be done to strengthen the disclosure of detailed information on various liquidity risk measures. Greater transparency would help the market and authorities assess the robustness of individual institutions' liquidity management practices, potentially allowing official liquidity support to be minimized, better targeted, and more effectively provided.

A defining characteristic of the 2007–08 financial crisis was the simultaneous and widespread dislocation in funding markets—that is, the inability of multiple financial institutions to roll over, or obtain, new short-term funding.[1] The crisis further revealed that liquidity risk at financial institutions had significant consequences for financial stability and macroeconomic performance, in part through the banks' common asset exposures and their increased reliance on short-term wholesale funding. Liquidity risk management decisions made by institutions spilled over to other markets and other institutions, contributing to others' losses and exacerbating overall liquidity stress.

The freezing up of markets at the peak of the financial crisis required massive official intervention, cross-border coordination, and adjustments to central bank liquidity operations to stabilize the financial system and restore orderly market conditions. Central banks had to assume the role of the money market in distributing liquidity as banks and other lenders shunned each other, particularly beyond very short term maturities, because of rising counterparty risk concerns. Some central banks are still actively supporting the money market. The extent of official intervention is clear evidence that systemic liquidity risks were underrecognized and mispriced by both the private and public sectors.

To avoid a repeat of such events, the Group of Twenty (G-20) has called for increased liquidity buffers in financial institutions and more recently has requested an examination of the contributing role of so-called shadow banks to the buildup of systemic liquidity risk. A number of reforms and initiatives are under way to address shortcomings in financial institutions' liquidity practices. Under its new international regulatory framework for banks, known as Basel III, the Basel Committee on Banking Supervision (BCBS) has issued two new quantitative liquidity standards to be applied at a global level, and it has issued qualitative guidance to strengthen liquidity risk management practices in banks.

So far, however, policymakers have not established a macroprudential framework that mitigates systemwide, or systemic, liquidity risk. Systemic liquidity risk is the tendency of financial institutions to collectively underprice liquidity risk in good times when funding markets function well because they are convinced that the central bank will almost certainly intervene in times of stress to maintain such markets, prevent the failure of financial institutions, and thus limit the impact of liquidity shortfalls on other financial institutions and the real economy. If they ignore the tendency to underprice liquidity risk prior to the emergence of shortfalls and then intervene during times of systemic stress, central banks will reinforce these negative externalities and give financial institutions an incentive to hold less liquidity than needed.

Overall, macroprudential regulations that more accurately price the cost of official contingent liquidity support aim to eliminate unnecessary liquidity support by the public sector by better aligning private incentives. This realignment can be achieved in various ways, and this chapter does not take a stand on the type of macroprudential tool to be used: that is, whether a capital surcharge, a fee, a tax, or an insurance premium for contingent liquidity access is the best method. The first priority is to design some type of price-based assessment that would allow for a more effective private-public burden sharing of systemic liquidity risk management; the difficult issues of exactly how to implement it, and who should do so, can be tackled secondarily.

A macroprudential tool that charges an institution for its contribution to systemic liquidity risk presupposes a robust methodology for measuring such risk. This chapter suggests three separate measures of systemic liquidity risk, each of which can be used as the basis for a practical macroprudential tool that could help mitigate it. The methods are only illustrative—a "proof of concept"—in part because only publicly available data are used.

This chapter continues the October 2010 GFSR treatment of the same topic, which focused on funding markets and institutions' interaction through them. It put forward recommendations to strengthen infrastructure and correct market practices that generate simultaneous and widespread dislocation in funding markets. In contrast, however, this chapter focuses on how to measure systemic liquidity risk through time, an individual

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[1]See the October 2010 *Global Financial Stability Report* (GFSR) for a fuller discussion of the factors that contributed to systemic liquidity stress, including the role of various funding markets, and policy recommendations to strengthen the resilience of funding markets.

institution's contribution to this risk, and the tools to mitigate that risk. Overall, of course, financial sector reforms in this area need to tackle both financial markets and institutions. As noted in Chapter 2 of the October 2010 GFSR, greater use of central counterparties for repurchase agreements (repos) and better recording of over-the-counter transactions in repositories could help lower counterparty risk associated with systemic liquidity risk. That chapter further noted that some risks associated with collateral risk management in secured funding markets could be potentially addressed by requiring through-the-cycle haircuts or minimum haircut requirements for collateral. The chapter also noted that money market mutual funds and other nonbank institutions in the shadow banking industry contribute to systemic liquidity risk and require more oversight and regulation.

Systemically important financial institutions (SIFIs) contribute to systemic liquidity risks through size and connectedness with other financial institutions, including through excessive reliance on the same providers of liquidity and large common exposures to similar types of assets. Macroprudential instruments such as add-on capital surcharges or other tools to control systemic solvency risk among SIFIs should also help lower systemic liquidity risk. That is, if other means are effective in capturing the systemic liquidity risk, all the better, as then less reliance on mitigation techniques is needed. Any set of instruments would need to be regularly updated and sufficiently flexible and time-varying to account for all SIFIs and their changing contribution to systemic solvency and liquidity risk over time.

After providing a brief definition of systemic liquidity risk and the difficulty in measuring it, the chapter assesses the quantitative Basel III liquidity rules for banks and notes their limitations in mitigating systemic liquidity risk. It then presents three different approaches to measuring systemic liquidity risk that can be used to construct macroprudential tools to mitigate it. The chapter concludes with some policy recommendations and compares the prudential measures presented here with other recent proposals.

What Is Systemic Liquidity Risk?

Little progress has been made so far in addressing systemic liquidity risk in a comprehensive way. The slow progress reflects the rarity of systemic liquidity events, the changing and complex interactions between various types of institutions in funding markets, and the conceptual difficulty in modeling them.

The chapter takes the view that liquidity risk can materialize in two basic forms:

- Market liquidity risk, which is the risk that a firm will not be able to sell an asset quickly without materially affecting its price;[2] and
- Funding liquidity risk, which is the risk that a firm will not be able to meet expected cash flow requirements (future and current) by raising funds on short notice.

The two types of liquidity risks can interact with each other and, through markets, affect multiple institutions. In periods of rising uncertainty, the interaction can give rise to systemic liquidity shortfalls. A negative spiral between market and funding liquidity can develop whereby a sudden lack of funding leads to multiple institutions attempting to sell their assets simultaneously to generate cash. These correlated fire sales of assets may lead suppliers of liquidity to insist on higher margin and larger haircuts (the deduction in the asset's value used as collateral) as the value of collateral (assets pledged) declines. Creditors may become even less likely to provide funding, fearing insolvency of their counterparties, resulting in significant funding disruptions.[3] This self-reinforcing process can lead to downward cascades in asset prices and to further declines in a firm's net worth, morphing into a systemic crisis as many institutions become affected.

This interaction underscores the difficulty of disentangling the risk of systemic insolvency from that of systemic illiquidity because the two are closely linked. A key question is whether liquidity events emerge in isolation or whether they are caused by the heightened perception of rising counterparty and default risk of financial institutions. The analysis below uses various

[2]Market liquidity can also be defined as the difference between the transaction price and the fundamental value of a security (Brunnermeier and Pedersen, 2009).

[3]See Gorton and Metrick (2009), Brunnermeier and Pedersen (2009), and Shleifer and Vishny (2010) for a discussion of how margin spirals, increases in haircuts on repos, and fire sales affect a firm's ability to borrow, its solvency, and the overall fragility of the financial system.

techniques to attempt to better isolate the systemic liquidity component of a systemic financial crisis.

There is no commonly accepted definition of systemic liquidity risk. This chapter defines it as the risk of simultaneous liquidity difficulties at multiple financial institutions. Such institutions may include not only banks but all financial institutions that engage in maturity transformation by acquiring in markets short-term liabilities to fund longer-term assets and that are thus vulnerable to liquidity runs and shortfalls.

Will Liquidity Rules under Basel III Lower Systemic Risk?

This section evaluates the two proposed liquidity standards for liquidity risk management for banks by the BCBS under Basel III and assesses whether they will help alleviate systemic liquidity risk.

Basel III establishes two liquidity standards—a liquidity coverage ratio (LCR) and a net stable funding ratio (NSFR) to be introduced after an observation period and further refinements. Principles for liquidity risk management existed before the crisis, but these rules represent the first time that quantitative standards for liquidity risk have been set at a global level.[4]

The LCR aims to improve a bank's ability to withstand a month-long period of liquidity stress as severe as that seen in the 2007–08 financial crisis. The LCR is defined as the "stock of high-quality liquid assets" divided by a measure of a bank's "net cash outflows over a 30-day time period." The resulting ratio should be at least 100 percent. High-quality assets are mostly government bonds and cash, and a maximum of 40 percent of mortgage and corporate bonds may be of a certain lower credit quality. The size of the net outflow is based on assumed withdrawal rates for deposits and short-term wholesale liabilities and the potential drawdown of contingency facilities. The LCR assumes a 100 percent drawdown of interbank deposits and all other short-term financial instruments of less than 30 days' maturity.

This chapter could not evaluate the LCR primarily because it required information on the credit quality, ratings, and liquidity characteristics of the ratio's so-called Level II assets—such as covered bonds, rated corporate bonds, and agency debt—that are not publicly available. Furthermore, its analysis would require knowledge of the duration and composition of assets and liabilities, including off-balance-sheet exposures, to calculate the net cash flow impact of stress during a 30-day period. This information is also not available publicly.

The NSFR aims to encourage more medium- and long-term funding of the assets and activities of banks, including off-balance-sheet exposures as well as capital market activities, and thereby reduce the extent of maturity mismatch at the bank. In theory, this would lower a bank's probability of liquidity runs and associated default. The ratio is defined as a bank's available stable funding (ASF) divided by its required stable funding (RSF) and must be greater than 100 percent. It is intended to support the institution as a going concern for at least one year if it is subject to firm-specific funding stress.[5]

Impact of the Net Stable Funding Ratio on Globally Oriented Banks

An NSFR was calculated with publicly available data for each of 60 globally oriented banks in 20 countries and three regions (Europe, North America, and Asia). The institutions encompass commercial, universal, and investment banks. An additional 13 banks that became insolvent during the recent crisis were added to the sample to analyze the predictive power of the NSFR.

To try to calculate a realistic NSFR, a number of assumptions had to be made on how to apply the Basel III weights, or factors, to the components making up the ASF and RSF. These assumptions reflected broad interpretations of the liquidity and stability characteristic of banks' balance sheets (Table 2.1).[6] The factors were applied uniformly and consistently across all banks. Overall, however, data issues remain

[4]The latest version of the framework was published in December 2010. An observation period will precede official implementation of the ratios as a minimum standard. In both cases, any revisions to the factors will be finalized one and a half years before their official implementation, which will be on January 1, 2015 for the LCR and January 1, 2018 for the NSFR.

[5]The metric is covered in more detail in BCBS (2010a).

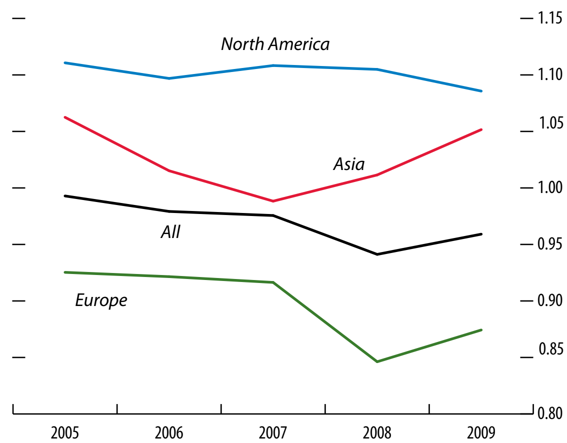
[6]Annual balance sheet data from Bankscope covering the period 2005–09 were used in addition to the banks' annual reports. Stable funding is required for all illiquid assets and securities held, regardless of accounting treatment (for example, trading versus available-for-sale or held-to-maturity designations).

a challenge in the analysis of the NSFR. The internal financial reporting systems at many banks are not consistent with the Basel categories. Further, the lack of harmonized public financial accounting data hinders a comparison of the rules across banks and jurisdictions.[7] Moreover, some Basel III definitions, such as the treatment of customer deposits and the notion of their stability, are not entirely clear.

Calculations of maturity mismatches, as proxied by the NSFR, deteriorated before and during the crisis (Figure 2.1).[8] The average NSFR ratio hovered just below 100 percent before the crisis, worsened in 2008, and then improved slightly in 2009. A regional breakdown shows that the NSFR at European banks declined during the crisis, with the ratio improving somewhat in 2009. The NSFR for North American banks declined slightly with the start of the crisis but remained above 100 percent, while Asian banks improved their ratio during the crisis, staying above 100 percent. The recent shortening in the maturity profile among some banks reflects a shorter-term funding structure, including the availability of cheap, safe, and ample central bank financing as well as the requirement to include some off-balance-sheet liquidity commitments on their balance sheets.[9]

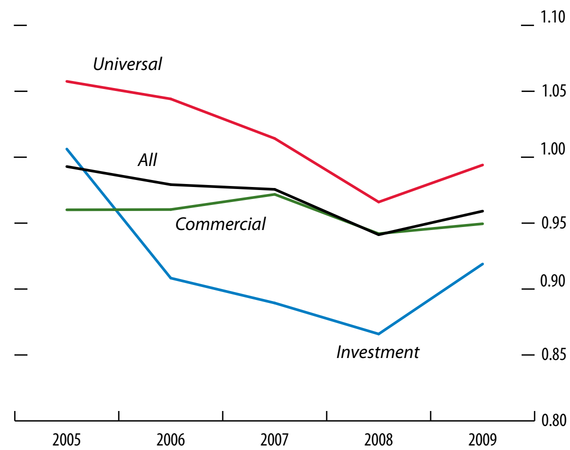
The NSFR declined more sharply for investment and universal banks than for commercial banks (Figure 2.2). The funding profiles improved in 2009 across business models, where universal banks reached the 100 percent threshold. For commercial banks, a key driver of the ratio is their exposure to illiquid loans, which carry a higher RSF factor. Investment banks and universal banks that have investment banking activities exhibit higher variation in the NSFR through time, in

Figure 2.1. Net Stable Funding Ratio by Region
(In percent)



Sources: Bankscope; and IMF staff calculations.

Figure 2.2. Net Stable Funding Ratio by Business Model
(In percent)



Sources: Bankscope; and IMF staff calculations.

[7]The treatment of derivatives is such a case. Banks operating under International Financial Reporting Standards (IFRS) report gross derivative positions, while those under generally accepted accounting principles (GAAP) report netted positions. This can make a difference of up to 20 percent of the balance sheet in some cases. The compromise adopted in this exercise in calculating the NSFR is to net the derivatives and apply a factor to the balance. Another case is decomposition of securities data for investment banks. Part of the securities held by investment banks is highly structured and illiquid, but a breakdown is not available. It is assumed that 30 percent of securities are illiquid or held to maturity, and require stable funding.

[8]Available data run only through the end of 2009.

[9]See Chapter 1 for a more detailed discussion of the refinancing risks of the banking sector.

Table 2.1. Factors Used in Calculations

Available Stable Funding	Factor	Required Stable Funding	Factor
Equity	1.00	Cash	0.00
Tier 2	1.00	*Customer loans*	0.75
Demand deposits	0.80	*Commercial loans*	0.85
Saving and term deposits	0.85	*Advances to banks*	0.00
Bank deposits	0.00	*Other commercial and retail loans*	0.85
Other deposits and short-term borrowing	0.00	*Other loans*	1.00
Derivative liabilities	0.00	*Derivative assets*	0.90
Trading liabilities	0.00	*Trading securities*	0.15
Senior debt maturing after one year	1.00	*Available for sale securities*	0.15
Other long-term funding	1.00	Held-to-maturity securities	1.00
Other noninterest-bearing liabilities	0.00	Investments in associates	1.00
Other reserves	1.00	Other earning assets	1.00
		Insurance assets	1.00
		Residual assets	1.00
		Reserves for nonperforming loans	1.00
		Contingent funding	0.05

Sources: Bankscope; and IMF staff calculations.
Note: Categories in italics are IMF staff judgments.

part reflecting their greater reliance on wholesale funding but also their more flexible business models that can adjust to changing circumstances.[10]

A cross-section of calculations for 2009 shows that the average NSFR is about 96 percent, just below the "greater than 100 percent" threshold, and that the estimated gap between the ASF and RSF for the 60 global banks is about $3.1 trillion—that is, if they were to attain an NSFR of greater than 100 percent, they would need to raise a total of $3.1 trillion in stable funds (Figure 2.3). Close to one-third of the banks each have an NSFR greater than 100 percent, and about half of the banks have an NSFR greater than 90 percent. In comparison, the impact study by the BCBS (2010b) finds that, for 94 large global banks, the average NSFR is 93 percent. For Europe, the Committee of European Banking Supervisors (2010) finds an average estimated NSFR of 91 percent for 50 large banks.

Finally, empirical evidence is mixed, at best, regarding the NSFR's ability to signal future failures due to liquidity problems (Box 2.1). For a sample of 60 banks, end-2006 data show that seven of the 13 failed banks had an NSFR ratio below 100 percent (with one bank significantly below), but overall, the banks that failed during the crisis are evenly distributed across the range of NSFRs. This empirical weakness could reflect assumptions made in the construction of the NSFR, given the lack of detailed data, or that a number of contingent claims, including those related to special investment vehicles, which created a significant drain on banks' liquidity, are not properly accounted for. The empirical outcome for the NSFR could also be weakened if failed banks in the sample suffered more from solvency problems and rising counterparty concerns than from liquidity problems.

[10]See Ötker-Robe and Pazabasioglu (2010) for a study on the impact of regulatory reforms on large complex financial institutions.

Pros and Cons and Limitations of Basel III in Addressing Systemic Liquidity Risk

The new liquidity standards are a welcome addition to firm-level liquidity risk management and microprudential regulation. Combined with improved supervision, these rules should help strengthen liquidity management and the funding structure of individual banks and thereby enhance the stability of the banking sector.

In addition, by raising liquidity buffers and reducing maturity mismatches at individual firms, Basel III indirectly addresses systemic liquidity risk because it reduces the chance that numerous institutions will have a simultaneous need for liquidity. Moreover, the new standards penalize exposures to other financial institutions; in this way they reduce the interconnectedness in the financial system and hence the likelihood of interrelated liquidity losses.

A well-calibrated LCR and NSFR can contribute to the liquidity and funding stability of banks. Further quantitative impact studies are needed to ensure that the factors in the construction of the NSFR are desirable from a financial stability perspective. Moreover, policymakers need to be sure that weights and factors that feed into the calibrations do not excessively restrict banks in their ability to undertake maturity transformation or in the ability of money markets to act as a buffer in helping institutions manage short-term liquidity. If the calibration is too restrictive, it could encourage migration of some banking activities into the less-regulated financial system, including toward shadow banks, and potentially accentuate rather than alleviate systemic risk. A way to address the latter problem would be to extend the quantitative liquidity requirements to these less-regulated institutions.

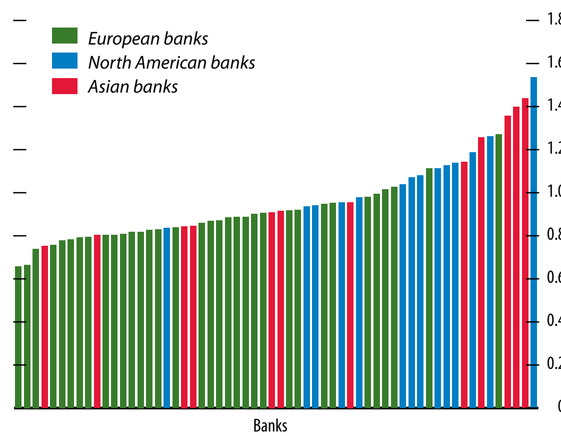
Policymakers also need to be mindful that the rules do not result in unintended consequences for financial stability. A too-stringent set of rules may force banks to take similar actions to reach compliance, resulting in high correlation across certain types of assets and concentrations in some of them. The LCR may lead to high holdings in eligible liquid assets that could effectively reduce their liquidity during a systemic crisis. Applying uniform quantitative standards across bank types and jurisdictions has its advantages, but the standards may not be suitable for all countries. For instance, a number of countries may not have the markets to extend term funding for banks given the absence of a bond market in domestic currency, and doing so would require banks to take on exchange rate risks.[11]

More broadly, at their core the Basel III rules are microprudential, aimed at encouraging banks to hold higher liquidity buffers and to lower maturity mismatches to lower the probability that any individual institution will run into liquidity problems. They are not intended or designed to mitigate systemic liquidity risks, where

[11]The BCBS is considering ways to account for the challenges faced by some countries that do not have a large enough domestic government debt market.

Figure 2.3. Net Stable Funding Ratio by Bank, 2009

(In percent)



Sources: Bankscope; and IMF staff calculations.

Box 2.1. How Well Does the Net Stable Funding Ratio Predict Banks' Liquidity Problems?

Although the net stable funding ratio (NSFR) was not designed as a predictor of liquidity difficulties, it is useful to ask whether banks that failed during the crisis had NSFRs that under Basel III would have been deemed deficient prior to their failure—that is, well below 100 percent. The analysis shows that the NSFR may have some capacity to signal future liquidity problems, but it would have done so inconsistently prior to the 2007–08 crisis.

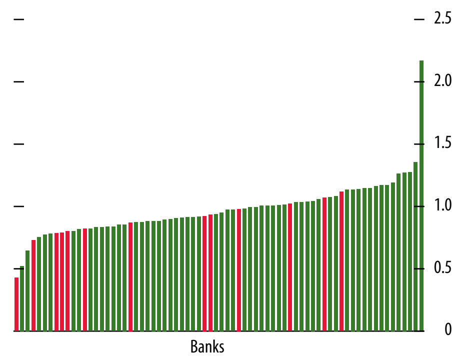
The predictive power of the NSFR for liquidity problems ahead of the 2007–08 financial crisis is explored by calculating the end-2006 NSFR of 60 banks. The exercise also includes 13 failed banks. The challenge in any such analysis is to be able to separate liquidity from solvency problems. When a bank is perceived as insolvent, its funding options can quickly become circumscribed. Similarly, if a bank has severe liquidity problems, it may be forced to sell its assets at fire sale prices, accruing large losses with potential implications for its solvency.

Nevertheless, some studies show that problems at Northern Rock and HBOS, two U.K. banks that failed during the crisis, had less to do with credit-related problems than with funding risk due to their overreliance on securitization and short-term wholesale funding, including asset backed commercial paper, to fund longer-term illiquid assets.[1] Wholesale funding accounted for a considerable portion of the funding sources for these banks, and they were most vulnerable to the rapidly deteriorating conditions in the wholesale funding markets.

Note: This box was prepared by Turgut Kisinbay.

[1]See the October 2010 GSFR, *Financial Times* (2008), and Shin (2009).

Net Stable Funding Ratio Estimates for an Expanded Set Including Failed Banks, 2006
(In percent)



Sources: Bankscope; and IMF staff calculations.
Note: Failed banks are depicted in red.

The box figure suggests that, by itself, the NSFR may not be a reliable indicator of future bank liquidity problems; failed banks are close to evenly distributed across the range of NSFRs. The ambiguous result may in part be explained by possible data inconsistencies that can affect the calculation of the NSFR. This includes the different treatment of special purpose vehicles (SPVs). In most jurisdictions exposures to SPVs were reported off-balance sheet before the crisis, but recently they have been better captured in bank disclosures. The NSFR may still be indicative of potential liquidity problems, as half of the banks below the 80 percent level did have such problems. Nevertheless, other complementary indicators and tools are necessary to gauge liquidity risks.

the interactions of financial institutions can result in the simultaneous inability of institutions to access sufficient market liquidity and funding liquidity under stress. Unless the liquidity requirements are set at an extremely high level for all institutions, resulting in a prohibitive cost to the real economy, the possibility always exists that a systemic liquidity event will exhaust all available liquidity. In such circumstances, central bank support is warranted to assure that systemic liquidity shortfalls do not morph into large-scale solvency problems and undermine financial intermediation and the real economy.

Policymakers have not established a macroprudential framework that mitigates systemwide, or systemic, liquidity risk. A problem so far has been the lack of analysis of how to measure systemic liquidity risk and the extent to which an institution contributes to this risk.

Measures of Systemic Liquidity Risk and Potential Macroprudential Tools to Mitigate It

The section presents three separate methods that illustrate the possibilities for measuring systemic liquidity risk and for creating macroprudential tools to mitigate it. These tools are complementary to the Basel III liquidity standards and would accomplish two goals: (1) measure the extent to which an institution contributes to systemic liquidity risk; (2) use this to indirectly price the liquidity assistance that an institution would receive from a central bank. Proper pricing of this assistance would help lower the scale of liquidity support warranted by a central bank in times of stress.

The methods are (1) a systemic liquidity risk index (SLRI), that is, a market-based index of systemic liquidity based on violations of common arbitrage relationships; (2) a systemic risk-adjusted liquidity (SRL) model, based on a combination of balance sheet and market data and on options pricing concepts for a financial institution, to calculate the joint probability of simultaneous liquidity shortfalls and the marginal contribution of a financial institution to systemic liquidity risk; and (3) a macro stress-testing model to gauge the effects of an adverse macroeconomic or financial environment on the solvency of multiple institutions and in turn on systemic liquidity risk.

All three methods use publicly available information but vary in degree of complexity (Table 2.2). Although the focus here is on banks, given data limitations, the methodologies are sufficiently flexible to be used for nonbank institutions that contribute to systemic liquidity risk. Indeed, the proposals build on several strands of recent research that focus on the interactions between financial institutions and markets in the context of systemic liquidity risk.

All three methods combine a cross-sectional dimension (i.e., linkages in liquidity risk exposures across markets and institutions) and a time dimension (i.e., noting changes though time of the various components of liquidity risk) in measuring systemic liquidity risk. Both elements capture developments over time in key market liquidity and funding liquidity variables, including volatilities and correlations for a host of financial instruments and markets, and direct and indirect linkages through common exposures to funding market risks. While the macroprudential measures derived from the techniques are not explicitly countercyclical—that is, changing over time in the opposite direction of the cycle—they can be adjusted in ways that allow for this.

The development of the associated macroprudential tools is in early stages. Ideally, any such tool would need to be based on a robust measure of systemic risk and allow for extensive backtesting; it would have to be risk adjusted so that institutions that contribute to systemic liquidity risk through their interconnectedness or through their impact pay proportionately more; it should further be countercyclical and time varying—that is, it should offset procyclical tendencies of liquidity risk and change in line with changes to an institution's risk contribution; and finally it should be relatively simple and transparent and not too data intensive to compute and implement. The suggested approaches in this chapter vary in the degree to which they satisfy such criteria.

Systemic Liquidity Risk Index

The new market-based index of systemic liquidity risk presented here exploits the fact that a breakdown of various arbitrage relationships signals a lack of market and funding liquidity. From daily market-based observations, this measure uncovers violations of arbitrage relationships that encompass identical underlying cash flows and fundamentals that are traded at different prices. Constructed using a common-factor approach that captures the similar characteristics of these violations in arbitrage relationships, the index offers a market-based measure of systemic liquidity risk. Traditionally, market-based measures have been used only to monitor market liquidity conditions in various markets (Table 2.3). The approach here integrates these multiple measures and incorporates the observation that they are connected to funding liquidity.

Under normal market conditions, similar securities or portfolios that have identical cash flows are expected to have virtually no difference in price except for relatively constant and small differences reflecting transaction costs, taxes, and other micro features. Any larger mispricing between similar assets should typically be exploited by financial investors through arbitrage strategies (such as short selling the overpriced asset and using the proceeds to buy the underpriced asset). Because these arbitrage strategies are considered virtually risk free, investors are able to obtain funding easily to ensure that violations of the law of one price quickly disappear.

Table 2.2. Main Features of the Proposed Methodologies

Features	Systemic Liquidity Risk Index (SLRI)	Systemic Risk-adjusted Liquidity (SRL) Model	Stress-testing (ST) Systemic Liquidity Risk
Indication of systemic liquidity risk	Sharp declines in the SLRI.	Joint probability that firms will experience a funding shortfall simultaneously (i.e., all risk-adjusted net stable funding ratios (NSFRs) fall below 1 at the same time).	Probability that a given number of banks end stress test with negative net cash flow.
Dimension	Time-series and cross-sectional	Time-series and cross-sectional	Time-series and cross-sectional
Macroprudential tools	Insurance premia used to assess institutions for their exposure to systemic liquidity risk.	Price-based macroprudential insurance premia and/or capital surcharge—used for costing contribution of an institution to systemic liquidity risk.	Capital surcharge used to minimize the probability of triggering a liquidity run for a bank.
Modeling technique	Exploits breakdowns of arbitrage relations, signaling market participant's difficulties in obtaining liquidity. Uses principal components analysis.	Uses advanced option pricing to convert an accounting measure of liquidity risk (NSFR) into a risk-adjusted measure of liquidity risk at market prices, and, thus, is forward-looking by definition.	Derives banks' net cash flows as the result of a stress test. Uses Monte Carlo simulation, network analysis, valuation equations for bank positions, and assumptions about a bank creditors' funding withdrawal response to solvency concerns.
Stochastic or deterministic assessment of liquidity risk	Stochastic, based on bank's equity volatility associated with the SLRI.	Stochastic, based on the exposure to funding shocks, which takes into account the joint asset-liability dynamics in response to changes in market rates.	Stochastic , based on banks' probability of default and bank creditors' response to solvency concerns.
Market/Transaction based	Market-based.	Market-based.	On- and off-balance-sheet-transaction based.
Treatment of funding and market liquidity risks	Indirectly. The SLRI is used to measure heightened market and funding liquidity risks.	Market and funding risks are embedded in equity prices, funding rates, and in their volatility.	Explicit modeling of funding and market liquidity risks using behavior observed during the recent crisis.
Treatment of solvency-liquidity feedbacks	Attempts to isolate counterparty risk to create a clean measure of liquidity risk.	There is no explicit treatment of the impact of solvency risk on liquidity risk. However, the derived risk-adjusted NSFR embeds a recognition that banks are vulnerable to solvency risks.	Integrates solvency and liquidity risks explicitly as well as second round feedback between them.
Treatment of channels of systemic risk	Not modeled directly.	Estimates the non-linear, non-parametric dependence structure between sample firms so linkages are endogenous to the model and change dynamically.	Captures institutions' common sources of asset deterioration—including price spirals driven by asset fire sales, network effects, and contagion.
Ease of computation	Econometrically simple and easy to compute.	Econometrically complex and time consuming.	Econometrically complex and time consuming.
Data requirements	Based on publicly available market data. Can be applied to any institution and system with publicly traded securities. No use of supervisory data.	Minimal use of supervisory data. Approach relies on pre-defined prudential specification of liquidity risk (e.g., NSFR) to assess the impact of maturity mismatches but can be directly linked to non-diversifiable liquidity risk, such as the SLRI.	Can be applied to any institution/system, even those that are not publicly traded. Requires detailed supervisory data, including data to assess underlying credit risks of institution assets.

Source: IMF staff.

However, in turbulent markets, arbitrage can break down. During the recent financial crisis, many arbitrage relationships were violated for relatively long periods. In currency markets, violations of covered interest rate parity (CIP) occurred for currency pairs involving the U.S. dollar. In interest rate markets, the swap spread, which measures the difference between Treasury bond yields and LIBOR swap rates, turned negative (IMF, 2008). In interbank markets, basis swaps that exchange different maturity LIBOR rates (for example, three-month for six-month) deviated from their close-to-zero norm. In credit markets, the CDS-bond basis, which measures the difference between credit default swaps (CDS) and implied credit spreads on cash bonds, turned negative.

Various factors may explain the breakdowns in arbitrage relationships that occurred during the crisis. As many of these relationships involve a fully funded (cash)

Table 2.3. Indicators for (Systemic) Liquidity Risk Monitoring[1]

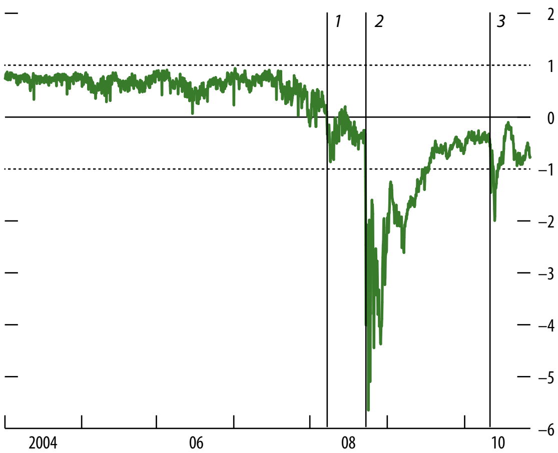
Indicators	Unsecured interbank rate	Interest rate derivatives	Repo spread	Margins and haircuts on repo collateral	Forex swap rate	Access to central bank liquidity facility
Examples	LIBOR-OIS spread, Euribor-OIS spread, TED spread, LIBOR rate spread-UST repo rate spread.	The probability distribution of LIBOR-OIS spread using derivatives (e.g. interest rate cap).	UST-repo rate, agency MBS repo rate-UST repo rate, U.S. asset-backed CP yields-UST.	Margins and average haircuts for various repo collateral assets.	Short-term foreign exchange swap implied interest rate-LIBOR, longer-term cross-currency basis swap-LIBOR.	Volume of bids for central bank facility at rates above expected marginal rate.
Primary type of liquidity risk	Funding liquidity.	Funding liquidity.	Funding liquidity.	Funding and market liquidity risk.	Foreign exchange funding risk.	Funding liquidity.
Pros	Widely used, easily available in most countries.	Provides probability assessment of liquidity stress events, forward looking.	Measures funding costs that are almost free of counterparty concerns.	Indicate the linkages between market liquidity of collateral and funding liquidity.	Indicates currency funding mismatch.	Measures funding liquidity risks with limited influence of market liquidity.
Cons	Influenced by counterparty risks. Not a representative measure of funding costs where repos are widely used.	Influenced by counterparty risks.	Influenced by market liquidity risk of collateral assets. Limited data availability (most are traded over the counter).	Difficult to collect and aggregate data. Difficult to disentangle liquidity and counterparty risks.	Influenced by counterparty risks.	Requires access to confidential data.
Indicators	**Monetary aggregate**	**Spreads between assets with similar credit characteristics**	**Violation of arbitrage conditions**	**Liquidity Mismatch Index**	**Market microstructure measures**	
Examples	Rate of change of the aggregate balance sheet of the financial institutions in a system. Aggregate money supply or credit growth.	UST off the run-on the run; German government guaranteed agency bonds-sovereign yields.	CIP-basis, CDS-bond basis.	Net stable funding ratio and liquidity coverage ratio.	Bid-ask spread, turnover, depth, and volume.	
Primary type of liquidity risk	Macro stock of liquidity.	Market liquidity risk.	Market liquidity risk.	Balance sheet liquidity mismatch risk.	Market liquidity risk.	
Pros	Highlights macro-level links among asset prices, financial institution net worth, and supply of credit to the economy from financial institutions.	Clean measure of market liquidity, controls for counterparty risks.	Signals abnormal financial market conditions.	Attempting to summarize overall liquidity risks of each financial institution. Useful for macroprudential supervision.	Long history in being used to assess market liquidity indicators and pricing impact of liquidity.	
Cons	For accurate measurement, need to look at overall "money" created by all financial institutions including nonbanks.	Available only for specific markets.	Influenced by counterparty risk.	Calibration of weighting system for each asset and/or liability component remains to be done.	Includes transaction costs and may not be related or sensitive to systemic liquidity shocks.	

[1]This table was prepared by Hiroko Oura.
Note: CIP = covered interest rate parity; CDS = credit default swap; CP = commercial paper; Euribor = euro interbank offered rate; OIS = overnight index swap; UST = U.S. Treasury bill.

instrument and one or more unfunded over-the-counter (OTC) derivative positions, concerns over counterparty risk on the OTC derivative may have rendered the arbitrage more risky. Another possibility is that funding costs on the cash instrument were responsible for the deviations, as investors were unable to quickly raise or reallocate funds. That inability in turn could have been due to a rise in market liquidity risk: investors became unable to rebalance their portfolios without incurring a significant cost because of fire sale conditions. Or it could have been due to a rise in funding risk: investors became unable to borrow or did not have sufficient capital to take advantage of the arbitrage opportunities.[12]

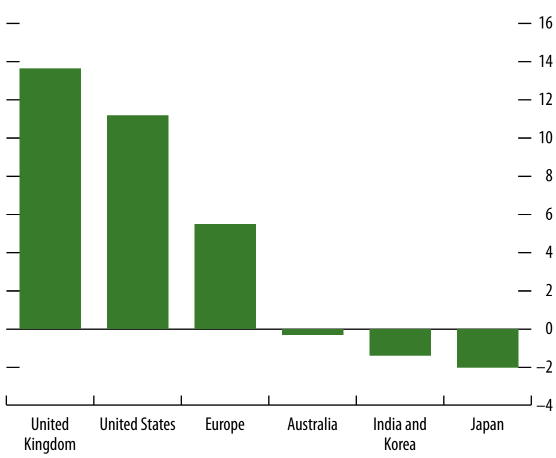
[12]Gromb and Vayanos (2010) examine the impact of banking losses on other financial intermediaries' ability to raise funds to take advantage of arbitrage opportunities.

Figure 2.4. Systemic Liquidity Risk Index
(In standard deviations)



Sources: Bloomberg L.P.; Datastream; and IMF staff estimates.
Note: The dotted band depicts +/– standard deviation around the zero line. Dates of vertical lines are as follows: 1—March 14, 2008, Bear Stearns rescue; 2—September 14, 2008, Lehman Brothers failure; and 3—April 27, 2010, Greek debt crisis.

Figure 2.5. Average Sensitivity of Volatility of Banks' Return on Equity to Systemic Liquidity Risk Index



Sources: Bloomberg L.P.; Datastream; and IMF staff estimates.
Note: The axis displays sensitivity. The sensitivity accounts for the impact of changes in the SLRI on the measured volatility of stock returns. The sensitivity for each region reflects the average sensitivity for all the individual banks in the corresponding area. Details about the methodology used to compute these sensitivities are available in Annex 2.1.

After controlling for counterparty risk, a number of studies point to liquidity frictions as the driving factors for violations in many of these trading relationships.[13] Those frictions prevent arbitrage strategists from liquidating positions without incurring large costs, or prevent them from raising capital and funding quickly, or make them unwilling to take large positions because of uncertain asset valuations. Consequently, the magnitude of the pricing discrepancy can be affected by the availability of funding and market liquidity and the ability of investors to process information.

The following analysis examines arbitrage violations of CIP in the foreign currency markets, of the CDS-bond basis in the nonfinancial corporate debt market, the on-the-run versus the off-the-run spread for U.S. treasuries, and of the swap spread in the money market (see Annex 2.1 for a description of the methodology and a potential application to a macroprudential tool). In total, the analysis covers 36 series of violations of arbitrage in three securities markets at various maturities. The principal components analysis (PCA) identifies a common factor across the three asset classes that can explain more than 40 percent of the variation in sample. The time series predictions of this common factor (using the underlying data) can be empirically constructed and are interpreted here as a systemic liquidity risk index (SLRI)—that is, a measure to identify the simultaneous tightening of global market liquidity and funding liquidity conditions (Figure 2.4). Sharp declines in the index are associated with strong

[13]When controlling for counterparty risk (typical measures are the CDS index, the volatility index, and dispersions of quotes for LIBOR), Coffey, Hrung, and Sarkar (2009) and Griffoli and Ranaldo (2010) find that liquidity frictions played a central role in the violations of CIP, as dollar funding constraints kept traders from arbitraging away excess returns. Bai and Collin-Dufresne (2010) find that liquidity factors were critical in explaining the difference in the CDS-bond bases across 250 firms in the United States. Schwarz (2010) finds that liquidity risk explains two-thirds of the LIBOR-OIS spread during the crisis. Mitchell and Pulvino (2010) point to the importance of funding restrictions by institutional investors as impeding the opportunities for arbitrage in closed-end funds. Chacko, Das, and Fan (2010) develop a new liquidity risk measure using exchange-traded funds, which attempts to minimize measurement error, in particular with regard to credit risk. Their liquidity measure can explain both bond and equity returns, and they provide evidence that illiquidity is Granger-caused by volatility in financial markets, but not the reverse. Fontaine and Garcia (2009) use data on the U.S. government debt market to develop a systemic liquidity risk measure.

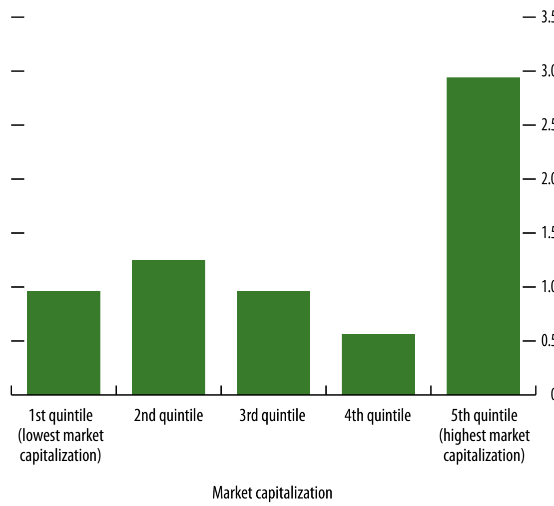
deviations from the law of one price across the many assets considered and thus suggest a drying up of market and funding liquidity at the global level.

A normalized SLRI is next used to examine whether it can explain the differential effect that systemic illiquidity may have had on banks during the crisis.[14] Overall, the results do not show a strong relationship between the SLRI and a set of 53 globally oriented banks' return on equity (see Box 2.2 for a discussion of the results). However, there is evidence that banks' equity is more sensitive to the SLRI when the banking sector is in distress, suggesting that there may be a relationship with return volatility. Indeed, the analysis finds that declines in the SLRI are correlated with increased volatility in bank equity returns, with some region's banks more sensitive than others (Figure 2.5). This association could reflect greater investor concern over the riskiness of an institution's prospects, including its liquidity risk. Similarly, the analysis finds a strong relationship between the SLRI and equity volatility, controlling for the size of banks, as proxied by market capitalization (Figure 2.6). Interestingly, it is the largest banks that have return volatility most sensitive to liquidity risk, suggesting size may be one possible criterion to determine the banks that should receive more supervisory attention for their liquidity management. Finally, the analysis does not find a strong relationship between a bank's funding risk, as reflected by the NSFR, and the SLRI. This seemingly counterintuitive result can be explained by noting that the NSFR is by design a microprudential indicator measuring structural funding problems in an institution, and hence it is unlikely to adequately proxy for the same type of systemic liquidity risk in the index (Figure 2.7).

Finally, the SLRI can be used to develop a liquidity surcharge scheme designed to assess banks and nonbanks for the costs associated with their exposure to systemic liquidity risk. The proceeds from the surcharges could be accumulated perhaps at the central bank or government or at a private sector insurer. The size of an individual institution's charge would be determined by calculating how much the institution's risk is associated with systemic liquidity risk, condi-

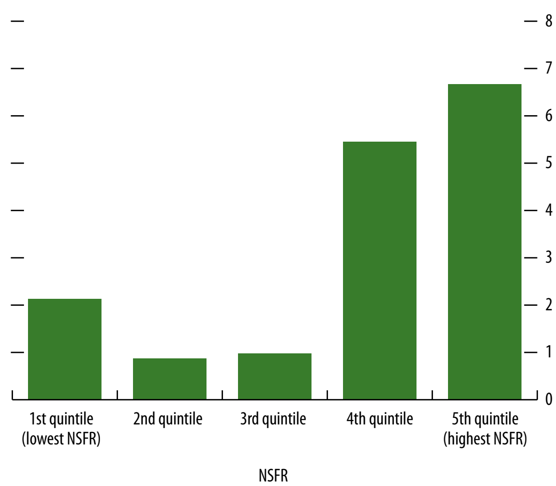
[14]The normalization subtracts from the daily SLRI the mean SLRI over the sample period and divides it by its standard deviation.

Figure 2.6. Sensitivity of Volatility of Banks' Return on Equity Based on Market Capitalization to Systemic Liquidity Risk Index



Sources: Bloomberg L.P.; Datastream; and IMF staff estimates.
Note: The axis displays sensitivity. The sensitivity accounts for the impact of changes in the SLRI on the measured volatility of returns on portfolios of individual banks ranked according to their market capitalization. Details about the methodology used to compute these sensitivities are available in Annex 2.1.

Figure 2.7. Sensitivity of Volatility of Banks' Return on Equity Based on Net Stable Funding Ratio (NSFR) to Systemic Liquidity Risk Index



Sources: Bloomberg L.P.; Datastream; and IMF staff estimates.
Note: The axis reflects sensitivity. The sensitivity accounts for the impact of changes in the SLRI on the measured volatility of returns on portfolios of individual banks ranked according to their NSFR. Details about the methodology used to compute these sensivities are available in Annex 2.1.

Box 2.2. How Well Does the Systemic Liquidity Risk Index Explain Banks' Liquidity Problems?

The systemic liquidity risk index (SLRI) may have some promise for signaling liquidity problems, in particular when banks are under stress. This box examines the sensitivity of bank returns to the SLRI and the relation of that sensitivity to certain bank characteristics.

The SLRI introduced in the chapter is intended to gauge a systemic tightening in market and funding liquidity. Its ability to do so can be assessed in relation to bank stock returns and volatility in those returns.[1]

The analysis suggests that, for the most part, the SLRI has no strong relationship with stock returns after controlling for market conditions. However, the ability of the SLRI to explain variations in bank credit default swap (CDS) spreads suggests that systemic liquidity shortages adversely affect returns on equity at individual banks when the banking sector as a whole is in distress.

Empirical evidence also indicates that aggregate liquidity conditions reflected by the SLRI affect the volatility in bank stock returns.[2] Lower systemic liquidity is associated with an increase in the volatility of bank returns after controlling for other aggregate risk factors and for bank-specific measures of risk like the CDS spread. The association suggests that, as investor uncertainty over a bank's prospects increases, tighter funding conditions have a greater impact on the bank's earnings outlook. The analysis also finds that banks in Denmark, the euro area, Norway, Switzerland, the United Kingdom, and the United States are more exposed, on average, to a decline in the SLRI (signaling a tightening of liquidity conditions) than are banks in Japan, probably because of the more-liquid balance sheets of Japanese banks.

The analysis also examines whether particular bank characteristics are associated with exposure to the SLRI. Two characteristics are examined: (1) market capitalization, as a proxy for size and for whether large banks are more vulnerable to stressed systemic liquidity conditions than smaller banks and (2) the NSFR, as a proxy for funding mismatches—that is, whether banks with a lower NSFR are more exposed to stressed systemic liquidity conditions. Results show some positive relationship between size and exposure to liquidity risk, in particular for the very small and very large banks in the sample. On the second point, the analysis finds a counterintuitive relation between the NSFR and the SLRI. The set of banks with a higher NSFR seem to be more exposed to the SLRI, as the volatility of their daily stock returns increases substantially more (relative to their peers) when the SLRI declines (that is, when it indicates a tightening of liquidity conditions). One would expect to find that banks with a relatively low maturity mismatch (that is, a high NSFR) to be less susceptible to systemic liquidity shortages than banks with a high mismatch, though the measures may be capturing somewhat different concepts of liquidity.

Several robustness checks did not change the main findings. For instance, the SLRI is not materially affected if some of the violations of arbitrage in certain markets are omitted from its computation, such as the swap spread, which is more prone to counterparty risk relative to other arbitrage relationships considered. Additionally, even after controlling for the direct SLRI effects of the average CDS spread for global banks, the resulting SLRI can still explain the riskiness of individual banks.

Note: This box was prepared by Tiago Severo.

[1]The discussion here is in terms of the normalized SLRI. The normalization subtracts the mean of the SLRI from the daily SLRI over the sample period and divides by its standard deviation.

[2]This was found by applying an ARCH (1) process, but the results are also robust to other model specifications such as GARCH, EGARCH, and GJR-GARCH.

tioning the calculation on relatively stressful periods.[15] Such charges should reflect the expected cost to the government of supporting banks' liabilities under scenarios of systemic liquidity stress. To be effective, the charge would be imposed on all institutions that are perceived as benefiting from implicit public guarantees and hence should cover banks and nonbanks that contribute to systemic liquidity risk.

[15]Technically, this would reflect the degree to which each institution's implicit put value on its assets changes as the volatility of equity increases due to systemic liquidity stress as measured by the SLRI.

A Systemic Risk-Adjusted Liquidity Model

The new SRL model presented here combines option pricing with market and balance sheet data to estimate an institution's liquidity risk and then uses this measure to calculate the joint probability of all institutions experiencing a systemic liquidity event (Jobst, forthcoming). This joint probability can then be used to measure an individual institution's contribution to systemic liquidity shortfalls (for all institutions) over time and to calculate a potential surcharge or insurance premium. This contribution to overall systemwide liquidity shortfalls will depend on an institution's funding and asset structure and its interconnectedness.

The innovation of the SRL model is its use of contingent claims analysis (CCA) to measure liquidity risk. CCA is widely applied to measure and evaluate solvency risk and credit risk at financial institutions. In this model, CCA combines market prices and balance sheet information to compute a risk-adjusted and forward-looking measure of systemic liquidity risk. In this way, it helps determine the probability that an individual institution will experience a liquidity shortfall and also helps quantify the associated loss when the shortfall occurs (see Annex 2.2 for a more detailed discussion of the approach).

The SRL model uses as a starting point the current Basel III quantitative regulatory proposal aimed at limiting maturity transformation—the NSFR. The components of the NSFR—available stable funding (ASF) and required stable funding (RSF)—are each transposed into a risk-adjusted and time-varying measure. Doing so permits an institution's net exposure to the risk of liquidity shortfalls to be quantified. The net exposure depends on changes to market perceptions of risk, which can be derived from an institution's equity option prices and from its asset and liability structure. Changes to various risk factors that affect the ASF and RSF (such as volatility shocks in both asset returns and funding costs and the joint dynamics between them) can result in significant losses for individual institutions. Those losses can then be quantified by viewing the liquidity risk as if it was a put option written on the NSFR with a strike price of 1 (the lower threshold that banks will be mandated to maintain under the NSFR).

The SRL model was applied to 13 commercial and investment banks in the United States; firm-level data were obtained from annual financial statements covering end-2005 to end-2009. The variations in the components of the NSFR—that is, in the ASF and RSF—were used to compute the market-implied expected losses due to liquidity shortfalls under stressed conditions.[16] The results suggest that these individual expected losses can be extreme (Figure 2.8).

These results provide important insights for policymakers: the NSFR (whether as an accounting measure or a risk-adjusted measure) does not capture the risk of potential liquidity shortfalls under extremely stressed conditions. The median of the risk-adjusted NSFR for the 13 banks stays above 1 (Figure 2.8). In contrast, the median expected losses generated by the SRL model suggests that banks have become more vulnerable to extreme liquidity shocks and that their losses were higher during some time frames, namely in the run-up to the March 14, 2008, Bear Stearns rescue and around year-end 2008. Those results apply especially to firms dependent on funding sources that are more susceptible to short-term (and more volatile) market interest rates; that dependency, in combination with their relatively higher exposure to maturity mismatches, accentuates their vulnerability to liquidity risk. Because the SLR model takes into account the joint asset-liability dynamics between the ASF and RSF, it provides a far deeper analysis of the liquidity risk to which a firm is exposed than does looking at them separately or with only accounting data.

The systemic dimension of the SRL model of a particular institution is captured by three factors:

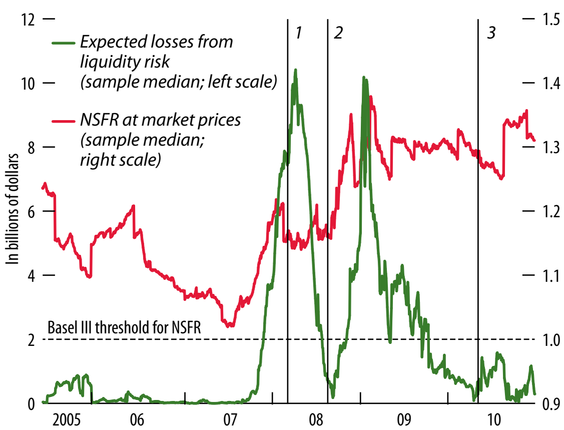
1. The market's evaluation of the riskiness of the institution (including the risk that the institution will be unable to service ongoing debt payments and offset continuous cash outflows). That evaluation, in turn, is based on a perception of the riskiness as implied by the institution's equity and equity options in the context of the current economic and financial environment.
2. The institution's sources of stable funding. Interest rates affecting both assets and liabilities are modeled as being sensitive to the same markets as the funding sources of every other institution. Changes in common funding conditions establish market-induced

[16]Extreme conditions were defined to be those that occur with a probability of 5 percent or less.

linkages among institutions. The proposed framework thus links institutions implicitly to the markets in which they obtain equity capital and funding.

3. Joint probability distributions. After obtaining risk-adjusted NSFRs for each institution, the likelihood that institutions will experience a liquidity shortfall simultaneously—that is, the probability that the NSFR for each institution falls to 1 or less at the same time—can be made explicit by computing joint probability distributions (see below). Hence, the liquidity risk resulting from a particular funding configuration is assessed not only for individual institutions but for all institutions within a system in order to generate estimates of systemic risk.

Figure 2.8. Illustration of Individual Expected Losses Arising from Liquidity Risk



Sources: Bloomberg L.P.; Bankscope; and IMF staff estimates.
Note: This figure is illustrative for a U.S. bank. Dates of vertical lines are as follows: 1—March 14, 2008, Bear Stearns rescue; 2—September 14, 2008, Lehman Brothers failure; and 3—April 27, 2010, Greek debt crisis. NSFR = net stable funding ratio.

Using the results for individual institutions, the SRL model can be applied to estimate systemwide liquidity risk in situations of extreme stress, which is defined as expected shortfall (ES). The accumulated expected losses of the individual institutions' risk-adjusted NSFR would have underestimated joint expected shortfalls between mid-2009 and mid-2010, where the red line exceeds the green line in Figure 2.9.[17] It would have failed to take into account the interlinkages in institutions' funding positions and their common exposure to the risk of funding shocks—that is, the systemic component. In contrast, the ES of the joint distribution of expected losses incorporates nonlinear dependence and the probability of extreme changes in funding costs. The results suggest that (1) if liquidity shortfalls happen simultaneously, the sum of individual losses does not account for their interdependence, and (2) contagion risk from this interdependence gets accentuated during times of extreme stress in markets. The joint expected shortfall may be easier to discern by looking at averages over specified periods (Table 2.4). During the crisis period from late 2008 to 2009, the joint expected shortfall was largest, as one would surmise.

The SRL results imply that some institutions contributed to systemic liquidity risk beyond the expected losses from their individual liquidity shortfalls. During the height of the crisis, the average contribution to extreme increases in system liquidity risk was higher

[17]In Figure 2.9, the green line represents the daily sum of individual, market-implied expected losses, and the red line indicates the joint expected shortfall. Both tail risks are measured so that the chances of such events are 5 percent or less.

than if only individual funding pressures were examined. These results illustrate the importance of including the systemic nature of liquidity risk when designing macroprudential frameworks.

The SRL model can be used to produce two price-based macroprudential tools—a capital surcharge and an insurance premium—that take into account the support that institutions would receive from a central bank in times of systemic liquidity stress and thus represent the individual cost of simultaneous liquidity shortfalls:

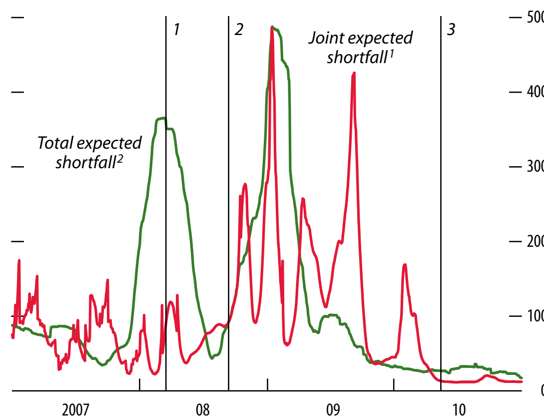
- The capital surcharge would be based on an institution's own liquidity risk (highest risk-based NSFR) or on its marginal contribution to joint liquidity risk, whichever of the two is higher.
- The insurance premium would reflect the chance that the institution, in concert with other institutions, falls below the minimum required NSFR of 1.

Table 2.5 presents the distribution of the capital charges over selected U.S. commercial and investment banks and Table 2.6 does so for the value of the insurance premium that would compensate for the joint expected shortfall associated with each bank. The capital charge represents the sum of money (in billions of dollars, as a percent of total capital, and as a percent of total assets of the 13 institutions in the system) that would be needed by the firms to offset liquidity shortfalls occurring when an NSFR of 1 is breached with a probability of 5 percent. Based on the calculations the selected U.S. institutions would need to set aside additional capital of about 0.7 percent of assets (median estimate) in 2010 to capture the externality they impose on others in the system. Basing the capital surcharge on the higher of two indicators (the maximum capital that offsets the amount of individual expected losses or the contribution of an institution to overall expected losses) is motivated by the fact that sometimes the individual component is higher and sometimes the contribution to the systemic risk is higher.

By contrast, the insurance premiums are calculated as the fair value over a one-year horizon to compensate for the liquidity support that would be needed to bring the NSFR above 1 during stressful times (occurring 5 percent of the time). The fair value insurance premium is derived as the actuarial value needed to exceed the present value of RSF over a risk horizon of one year. This premium is multiplied by all short-term uninsured

Figure 2.9. Illustration of Joint and Total Expected Shortfalls Arising from Systemic Liquidity Risk

(95 percent expected shortfall of risk-adjusted net stable funding ratio; in billions of dollars)



Sources: Bloomberg L.P.; Datastream; and IMF staff estimates.

Note: This figure is illustrative for 13 U.S. banks. Dates of vertical lines are as follows: 1—March 14, 2008, Bear Stearns rescue; 2—September 14, 2008, Lehman Brothers failure; and 3—April 27, 2010, Greek debt crisis.

[1]Expected shortfall at the 95th percentile of the multivariate distribution.

[2]Sum of individual expected shortfall estimates at the 95th percentile over a 30-day sliding window with daily updating.

Table 2.4. Joint Expected Losses from Systemic Liquidity Risk
(In billions of dollars)

	Pre-Crisis: end-June 2006 to end-June 2007	Subprime Crisis: July 1, 2007 to September 14, 2008	Credit Crisis: September 14, 2008 to December 31, 2009	Sovereign Crisis: January 1 to December 31, 2010
	Systemic Liquidity Risk[1]			
Minimum	14.8	22.4	36.1	17.4
Median	**65.4**	**68.9**	**150.3**	**31.4**
Maximum	191.8	148.5	486.2	60.2
Memorandum item				
Standard error	18.9	26.6	56.9	8.9

Sources: Bloomberg L.P.; Bankscope; and IMF staff estimates.
Note: This exercise was run on a selected set of 13 large U.S. commercial and investment banks.
[1]Expected shortfall at the 95th percentile of the joint distribution of expected losses.

Table 2.5. Capital Charge for Individual Liquidity Risk and Individual Contribution to Systemic Liquidity Risk
(In billions of dollars unless noted otherwise)

	Individual Expected Shortfall			Contribution to Joint Expected Shortfall					
	Stress Period: September 14, 2008 to December 31, 2009	Last Quarter (2010:Q4)	Average of 2010:Q1–Q4	Stress Period: September 14, 2008 to December 31, 2009	Last Quarter (2010:Q4)	Average of 2010:Q1–Q4	Capital Charge (maximum of (1)–(4))	Share of Total Capital (in percent)	Share of Total Assets (in percent)
		(1)	(2)		(3)	(4)			
	At 95th percentile			At 95th percentile					
Minimum	0.00	0.00	0.03	1.55	0.08	0.27	0.27	1.57	0.20
Median	**1.46**	**0.74**	**1.18**	**6.42**	**0.66**	**2.05**	**2.05**	**4.82**	**0.73**
Maximum	33.32	8.53	9.86	13.51	3.09	5.96	9.86	3.25	0.44

Sources: Bloomberg L.P.; Bankscope; and IMF staff estimates.
Note: This exercise was run on a selected set of 13 large U.S. commercial and investment banks. The last column matches the distributions of the individual capital charges and reported total capital of all sample institutions. In this case, the maximum capital charge for the worst bank in 2010 coincides with a disproportionately higher total capital amount, which reduces the percentage share of the capital add-on for systemic liquidity from 4.82 percent (median) to 3.25 percent (maximum). A similar circumstance applies to the calculations of shares of total assets. For details about the calculation of the capital charge, see Annex 2.2.

liabilities, i.e., the portion of deposits that is not covered by an insurance scheme. This reflects the cost of insuring the downside risk that no cash inflows are available to cover debt service obligations in times of stress.

Overall, the SRL model offers several potential benefits:

- It assesses an institution's liquidity risk from a particular funding configuration not only individually but in concert with all institutions to generate estimates of systemic risk. As such, it takes the systemic components of liquidity risk over time into account by estimating the joint sensitivity of assets and liabilities to changes in market prices.
- It treats liquidity risk as an exposure via a market-risk-adjusted value of the NSFR at high frequency rather than an accounting value as in the current Basel III framework.
- It measures the marginal contribution of each institution to total systemic liquidity risk at a given level of statistical confidence.
- It can be used to construct a capital charge or insurance premium for the institution's contribution to systemic liquidity risk.[18]

Moreover, the SRL approach can be used by supervisors within a stress testing framework to examine the vulnerabilities of individual institutions and the system as a whole to shocks to key asset and liability risk factors that underpin the NSFR. In adverse conditions,

[18]This contrasts with Perotti and Suarez (2009), who propose a charge per unit of refinancing risk-weighted liabilities based on a vector of systemic additional factors (such as size and interconnectedness) rather than the contribution of each institution to the overall liquidity risk and how it might be influenced by joint changes in asset prices and interest rates.

Table 2.6. Summary Statistics of Individual Contributions to Systemic Liquidity Risk and Associated Fair Value Insurance Premium

	Pre-Crisis: end-June 2006 to end-June 2007	Subprime Crisis: July 1, 2007 to September 14, 2008	Credit Crisis: September 14, 2008 to December 31, 2009	Sovereign Crisis: January 1 to December 31, 2010
	Individual contribution to systemic liquidity risk (at 95th percentile; in percent)[1]			
Minimum	1.2	0.6	1.0	1.7
Median	**6.8**	**4.5**	**8.3**	**7.6**
Maximum	13.4	35.1	16.7	14.5
Total	100.0	100.0	100.0	100.0
	Insurance cost based on reported exposure: Fair value insurance premium multiplied by uninsured short-term liabilities (In billions of dollars)			
Minimum	0.7	0.1	0.7	0.1
Median	**1.9**	**1.4**	**3.9**	**0.8**
Maximum	7.8	17.2	11.3	1.9

Sources: Bloomberg L.P.; Bankscope; and IMF staff estimates.

Note: This exercise was run on a number of selected U.S. banks. Insured deposits here are defined as 10 percent of demand deposits reported by sample banks. Note that the share of deposits covered by guarantees varies by country and could include time and savings deposits. Robustness checks reveal that reducing the amount of uninsured short-term liabilities does not materially affect the median and maximum. For details of the calculation see Annex 2.2.

[1]Each bank's percentage share reflects its contribution to the joint distribution of expected losses at the 95th percentile for a selected set of 13 large U.S. commercial and investment banks.

higher volatilities of market funding rates and lower correlation between funding rates can be mechanically imposed in the model to better examine short-term funding vulnerabilities.

A Stress-Testing Framework for Systemic Liquidity Risk

The third new approach to measuring systemic liquidity risk uses stress testing techniques.[19] The method presented below uses standard solvency stress tests as a starting point and adds, as an innovation, a systemic liquidity component. It can be used to measure systemic liquidity risk, assess a bank's vulnerability to a liquidity shortfall, and develop a capital surcharge aimed at minimizing the probability that any given bank would experience a destabilizing run.

The ST framework assumes that systemic liquidity stress is caused by rising solvency concerns and uncertainty about asset values.

The ST approach models three channels for a systemic liquidity event:

- A stressed macro and financial environment leading to a reduction in funding from the unsecured funding markets due to a heightened perception of counterparty and default risk;
- A fire sale of assets as stressed banks seek to meet their cash flow obligations. Lower asset prices affect asset valuations and margin requirements for all banks in the system, and these in turn affect funding costs, profitability, and generate systemic solvency concerns; and
- Lower funding liquidity because increased uncertainty over counterparty risk and lower asset valuations induce banks and investors to hoard liquidity, leading to systemic liquidity shortfalls.

This approach is consistent with the stress testing literature relating bank runs to extreme episodes of market-imposed discipline in which liquidity withdrawals are linked to banks' solvency risk (Table 2.7).

The ST methodology was applied to a set of 10 stylized banks, with June 2010 U.S. Call Report data used to define such banks. The stylized banks differ from each other in their initial capital ratios and sizes and in their risk profiles and loan concentrations.[20]

The framework first establishes the economic and financial scenarios in which these banks operate to capture the potential impact of changes in volatilities and correlations on asset values, and solvency risks (see Annex 2.3). Capital ratios and associated

[19]A detailed explanation of this methodology and its application in a stylized U.S. banking system can be found in Barnhill and Schumacher (forthcoming).

[20]The banks consist of two small banks (with assets concentrated in California and Florida-Georgia respectively); three middle-size banks (with assets concentrated in the west coast, midwest, and east coast); three large banks; and two megabanks that jointly account for just over 60 percent of total U.S. banking assets.

Table 2.7. Selected Liquidity Stress-Testing (ST) Frameworks

Framework	Bank of England	De Nederlandsche Bank	Hong Kong Monetary Authority	Proposed ST Framework
Data	Bank by bank financial reporting	Bank by bank financial reporting	Bank by bank financial reporting	Bank by bank financial reporting
Origin of liquidity shocks	Funding liquidity shock (cost and access) upon downgrade from solvency shocks (credit and market losses in macro ST).	Valuation losses and/or funding withdrawal to selected liquidity items.	Deposits are withdrawn in line with stressed probability of default (PD) (due to a loss from asset price declines) of the bank.	Asset price shocks. Bank liabilities are withdrawn following stressed PD of the bank.
Feedback, spillover, amplification effects	Linear, normal time linkages. Nonlinear effects using subjective but simple scoring system. Second-round effects through impact on asset price upon bank deleveraging and network effects.	Nonlinear effects as banks take deleveraging actions for larger shocks, and they feed back to asset valuation and funding availability (second-round effects).	Deleveraging to restore lost funding is costly owing to distress in asset markets. Interbank contagion (network effects).	Banks attempt to restore net cash flow by selling assets, which affect on market liquidity of the assets, further tightening funding liquidity (through higher haircuts)
Measurement of stress	Various standard metrics (solvency ratio, liquidity ratio, asset value, credit losses, ratings, profit, etc.).	Distribution of liquidity buffer across banks and across severity of shocks.	Probability of cash shortage and default; expected first cash shortage time; expected default time.	Solvency ratio; distributions of net cash flows and equity; joint probability of multiple institutions suffering from simultaneous cash shortfalls.
Origin of "systemic liquidity" characteristics	Initial macroeconomic shocks and various second-round effects.	From second-round effects.	From initial aggregate shock on asset prices, network effects.	Initial aggregate shock on asset prices and various second-round effects.
Pros	Nonlinear liquidity shocks and various second-round effects.	Nonlinear second-round effects.	Interaction among credit and funding and market liquidity risks.	Nonlinear second-round effects, assess joint probability of liquidity distress, and contribution of individual bank.
Cons	Includes subjective components to model nonlinearity.	Bank behavioral assumption and feedback effect formulated without strong micro foundation.	No feedback effects from distress on banks to asset prices.	Bank behavioral assumption and feedback effect formulated without strong micro foundation.

Note: Bank of England reflects the ST framework proposed by Aikmen and others (2009); De Nederlandsche Bank reflects the ST framework proposed by van den End (2008); and the Hong Kong Monetary Authority reflects the ST framework proposed by Wong and Hui (2009).

banks' default probabilities are simulated under the set of volatilities and correlations in two periods: a calmer 1987–2006 period; and a more volatile period from 2007 through the first quarter of 2010. With identical initial balance sheet positions, all banks have capital ratios that are lower in the second period than in the first. Applying this method could have signaled to supervisors the potential higher market concerns about bank solvency and the risk posed by the increasing reluctance to provide funding to these banks.

After generating a bank's capital ratio based on a solvency analysis, the exercise introduces liquidity risk. The withdrawal pattern of the period from 2007 to the first quarter of 2010 is used to develop a hypothetical relationship between a bank's probability of default and the rate of withdrawal of liabilities during that period. The relationship is determined under two cases. In case 1, withdrawal rates match those experienced by bank holding companies during the period.[21] In case 2, withdrawal rates match those experienced by investment banks; since investment banks have a very low level of insured deposits, this case provides a way to calibrate a more stressed scenario than that when banks are known to have insured deposits. Table 2.8 summarizes assumptions on total liability withdrawal rates associated with different default probability ranges for each case.

The stress test assesses whether banks faced with these withdrawal rates can deleverage in an orderly manner. Initially the banks with the higher probability of default stop lending in the interbank market and sell government securities and other liquid assets. Banks pay a higher cost of funding as they are forced to sell potentially less liquid assets, in particular if those assets are associated with a high

[21]During the crisis, some bank holding companies were able to increase their access to insured liabilities by converting large uninsured deposits into smaller insured deposits.

liquidity premium.[22] In this way, the model captures the interaction between funding and market liquidity and the second round feedback between solvency and liquidity risks.

In the 2007–10:Q1 financial environment under case 1 (bank holding company withdrawal rate), the probability that about three out of ten banks will simultaneously find themselves unable to make payments (that is, have a negative cash flow) is 3.8 percent (Table 2.9). That is, the risk of a systemic liquidity shock for this hypothetical U.S. banking system as of June 2010 would be low. In this example, the smaller banks are more affected than the larger ones because of their higher credit risk concentration and exposure to the macro risk factors that triggered the recent crisis. In addition, although banking failures occurred among smaller banks, their liquidity shortages did not lead to a systemic liquidity crisis. In the 2007–10:Q1 financial environment under case 2 (investment bank withdrawal rate), the probability that one-third of banks suffer a liquidity shortage increases to 12.7 percent.

Such potential liquidity shortages can create pressures for substantial reductions in bank loan portfolios and affect the economy. Indeed, both liquidity shortages and tighter lending standards and terms led to reductions in bank lending that were observed during the global crisis. In case 1, if the stylized banks facing liquidity runs reduce both securities and loan portfolios, the impact on total loans would be small (Figure 2.10, top panel, vertical axis). In case 2, by contrast, a potential liquidity run could lead to a significant reduction in total loans, of up to 43 percent, although with a low probability of less than 1 percent attached to this event (Figure 2.10, bottom panel, horizontal axis).

These ST results generally show that the ability of banks to weather a financial and economic shock and its impact on solvency and liquidity depends on a number of factors, including: (1) the size of the shock; (2) the adequacy of capital; (3) the availability of liquid assets; and (4) the exposure to short-term wholesale liabilities (in this model, interbank exposures). In this framework, if institutions were sufficiently capitalized and, hence, able to sell liquid assets and deleverage in an orderly manner, then there would be no systemic liquidity shock.

The methodology can be used to estimate an additional required capital surcharge or buffer to reduce the risk of future liquidity runs by lowering bank default risk. Given the assumed withdrawal relationships in Table 2.8, the additional capital buffer that would reduce to less than 1 percent the probability of a bank experiencing a liquidity run due to another bank failure over the next year is provided in Table 2.10. Of the 10 stylized banks, the small banks need to add the most capital because of their undiversified asset exposures to the real estate sector, where credit losses have been the highest.

Table 2.8. Withdrawal Rate Assumptions
(In percent)

Default Probability	Withdrawal Rate	
	Case 1	Case 2
10–20	5	7–10
20–35	10	14–21
> 35	25	42

Sources: SNL Financial; and IMF staff estimates.

Table 2.9. Probability of Banks Ending the Simulation with a Liquidity Shortage

Number of Banks	Probability	
	Case 1	Case 2
1	98.49	98.49
2	20.28	23.68
3	3.77	12.74
4	1.60	4.25
5	1.13	1.98
6	0.75	1.51
7	0.09	1.13
8	0.00	1.04
9	0.00	1.04
10	0.00	0.09

Sources: SNL Financial; and IMF staff estimates.

Summary and Policy Considerations

The financial crisis has highlighted the importance of sound liquidity risk management for financial

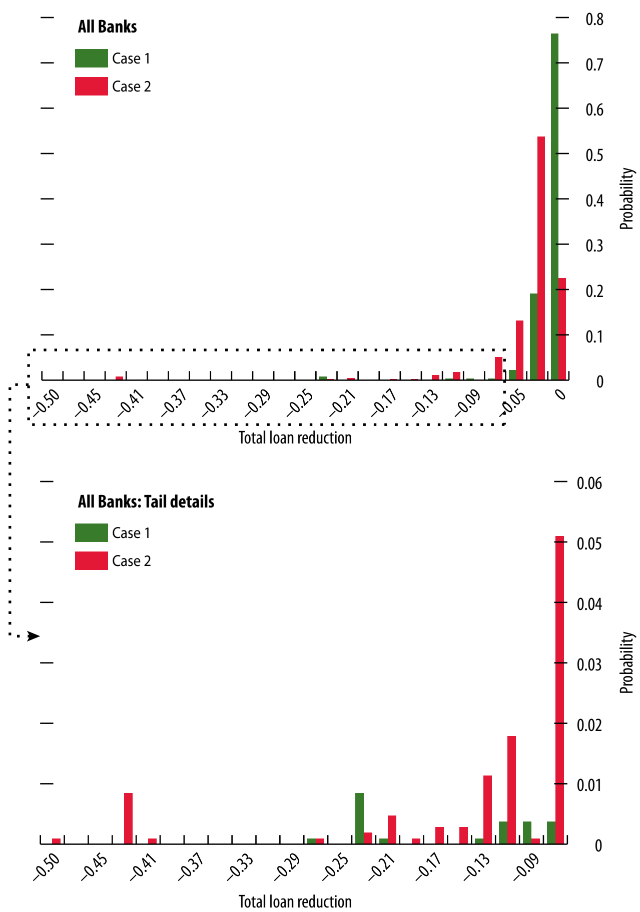
[22]Developments in bid-ask spreads in several securities markets during the 2000–09 period were used as a proxy for fire sale prices. At the peak of the crisis (September 2008), the size of the bid-ask spread was in the 5–10 percent range across different asset qualities, suggesting a discount factor of 3 to 5 percent to represent the loss suffered by the bank under distress when forced to liquidate assets. These values are in line with Coval and Stafford (2007), Aikman and others (2009), and Duffie, Gârleanu, and Pederson (2006).

stability and the need to address systemic liquidity risks. The new quantitative liquidity standards under Basel III—which are likely to be subject to some revisions—are a welcome addition to the tools available to regulators to achieve better liquidity risk management at individual banks. The prospective Basel III requirements for higher liquidity buffers and lower maturity mismatches at banks will better protect them from liquidity shocks. Higher liquidity buffers for all banks should also have the side-effect of lowering the risk of a systemic liquidity event because the extra liquidity buffer will lower the chances of multiple institutions simultaneously facing liquidity difficulties.

However, the liquidity rules under Basel III are, at their core, microprudential—the focus is on the stability of individual institutions—and not macroprudential, where the focus is on systemic risk. For instance, the chapter's analysis using publicly available data finds that one of the new Basel III measures, the NSFR, would not have indicated problems in the banks that ultimately failed during the 2007–08 crisis—at least some of which failed due to poor liquidity management and overuse of short-term wholesale funding. Therefore, more needs to be done to develop techniques to measure and mitigate systemic liquidity risks.

Although most of the formal attempts to address liquidity risk are microprudential in nature, a number of studies have begun to propose macroprudential tools to deal with its systemic nature (Table 2.11). For example, Brunnermeier and Pederson (2009) emphasize the usefulness of a capital surcharge to reduce liquidity risk associated with maturity mismatches, while Perotti and Suarez (2009; forthcoming) propose a mandatory tax on wholesale funding that could be used to fund an insurance scheme. Others, such as Goodhart (2009), have proposed to limit systemic externalities through a liquidity insurance mechanism in which access to publicly provided contingent liquidity would be permitted if a premium, tax, or fee were paid in advance. Acharya, Santos, and Yorulmazer (2010) suggest that a risk-based deposit insurance premium should not only reflect the actuarial fair value but should also include an additional fee imposed on systemically important institutions to reflect their excessive risk taking and the disproportionate cost they impose on others in the system. Most of these proposals do not, however, provide concrete advice

Figure 2.10. Total Loan Reductions
((As percentage of total loans)



Sources: Bankscope; and IMF staff estimates.
Note: The top panel shows the results of the bottom panel with a finer set of x-axis losses of loans and lower probabilities (y-axis).

Table 2.10. Capital Surcharges

	California	Florida-Georgia	West Coast	Midwest	East Coast	Large Bank 1	Large Bank 2	Large Bank 3	Mega Bank 1	Mega Bank 2
Initial capital ratio	0.104	0.057	0.124	0.104	0.080	0.134	0.124	0.095	0.101	0.088
Capital surchage	0.111	0.216	0.045	0.056	0.123	0.031	–0.011	0.049	0.046	0.026

Sources: SNL Financial; and IMF staff estimates.

Note: Capital surcharges required at time 0 for banks to have a 99 percent confidence level that at time 1 they would have less than a 10 percent probability of failing by time 2.

Table 2.11. Selected Regulatory Proposals for Managing Systemic Liquidity Risk

Author	Goodhart (2009)	Perotti and Suarez (2009; forthcoming)	Brunnermeier and others (2009)	Acharya and others (2010)	Cao and Illing (2009); Farhi, Golosov, and Tsyvinski (2009)	Valderrama (2010)
Proposal	Liquidity insurance: charge break-even insurance premium (collected including good times), monitor risk and sanction on excessive risk-taking.	Mandatory liquidity insurance financed by taxing short-term wholesale funding.	Capital charge for maturity mismatch.	Impose incentive-compatible tax (paid including good times) to access government guarantee (including for loan guarantees and liquidity facilities).	Minimum investment in liquid assets or reserve requirement.	Mandatory haircut for repo collaterals.
Pros	Premiums include add-on factors reflecting the systemic importance of each institution, which could lower systemic liquidity risk.	Each institution pays different charges according to their contribution to negative externalities, reflecting systemic risks.	Calibrating charges to reflect externality measures (e.g., CoVaR) for each institution.	Calibrating tax to reflect each institution's contribution to systemic risks.	If all the relevant institutions hold more liquidity, the system will be more resilient on aggregate. Furthermore, one could potentially introduce add-on requirements for systemically important institutions.	Delink the interaction between market and funding liquidity through cycle. Would affect a wide range of market participants in addition to banks.
Cons	No concrete examples how to calculate the premium.	No concrete example provided how to measure the systemic risk to the wholesale funding structure.	It is not clear whether a solvency-oriented CoVaR can be used for liquidity charge calculation.	No concrete examples how to implement the proposed tax implementation strategy. Refers to difficulties to measure externality or contributions to externality.	Additional analysis needed to fully incorporate systemic aspects due to interconnectedness and other externalities.	No concrete examples given on how to implement.

Source: IMF staff.

about how to calculate the amount of the fee or other surcharge nor how to implement it.

To complement these efforts, this chapter presents three methodologies that measure systemic liquidity risk in a way that can be used to calculate a fee or surcharge. They do so by calibrating an institution's contribution to system-wide liquidity risk and linking that contribution to an appropriate benchmark for an institution-specific charge. In doing so they attempt to account for the interactions between market and funding liquidity risks and those interactions over time (although they have not yet been devised to be explicitly countercyclical). The methodologies are developed here only with publicly available data, and hence the results are only broadly suggestive. With the more complete data available to supervisors and others, the methodologies could be adjusted for the greater accuracy necessary to become operational.

The chapter does not take a stand on which of the three methods is the best. Rather, through these illustrative calculations, it advances the broader point that supervisory policy should introduce some price-based macroprudential tool that would allow a more effective sharing of the private and public burdens associated with systemic liquidity risk management. It is unlikely at this stage of development that there is a single, best measure of systemic liquidity risk that can be directly translated into a macroprudential tool. Hence, the methods presented here should be viewed as complementary—examining the issues from different angles—to see which ones might be practically implementable.

Looking forward, therefore, the three methods presented here (and others) would need to be thoroughly examined to see how they would have performed before the crisis and whether they produce similar results in terms of surcharges or insurance premiums. The three different sample periods, the set of institutions on which reliable data was available, and the techniques used in this chapter are sufficiently different from each other that the surcharges or premiums presented here can only be viewed as crude approximations and are not directly comparable. These issues would need to be addressed in order to see whether comparable pricing estimates would result. Although the ease of future operational use will critically depend on data availability, their key attributes will also determine how quickly they can be put into place:

- The SRLI is the most straightforward to compute as it uses standard statistical techniques and market data, looks at violations of arbitrage condition in key financial markets, and can be used to monitor trends in systemic liquidity risk. The more difficult exercise will be to develop a method that links the index to an institution's contribution to systemic risk. Although the chapter outlines one way this can be done, it will require more analysis to ensure other factors are not confounding the results. Assuming this is satisfactorily demonstrated, the next step could be to construct a premium, and proceed with the difficult decisions about the amount of coverage, who would hold the proceeds, and when they would be used.
- The SRL model has the advantage of using daily market data and standard risk-management methods to translate individual contributions to systemic risk into a macroprudential measure. The SRL can produce timely (and forward looking) measures of risk of simultaneous liquidity shortfalls at multiple financial institutions. It can either be used as a standalone prudential instrument or be embedded into a ST framework. For the SRL to provide a robust methodology it would be important to assure that the funding liquidity risk measure applied (currently using the NSFR as proxy) be accurate.
- Finally, the ST framework is the one most familiar to financial stability experts and supervisors and thus the one that is easiest to implement in the short-run. As with other stress testing techniques, it captures systemic solvency risk by assessing the vulnerabilities of institutions to a common macro-financial shock, but then it adds this to the risk of liquidity shortfalls and assesses transmission of liquidity risk to the rest of the system through their exposures in the interbank market.

Despite which method is pursued to mitigate systemic liquidity risk, policymakers need to be mindful that any such macroprudential tool would need to be jointly considered in the broader context of other regulatory reforms that have been proposed, including possible charges or taxes for systemically important financial institutions or mandatory through-the-cycle haircuts and minimum margin requirements for secured funding. For instance, add-on capital surcharges or other tools to control systemic solvency risk could help lower systemic liquidity risk, thereby allowing possibly for less reliance on mitigation techniques that directly address liquidity.

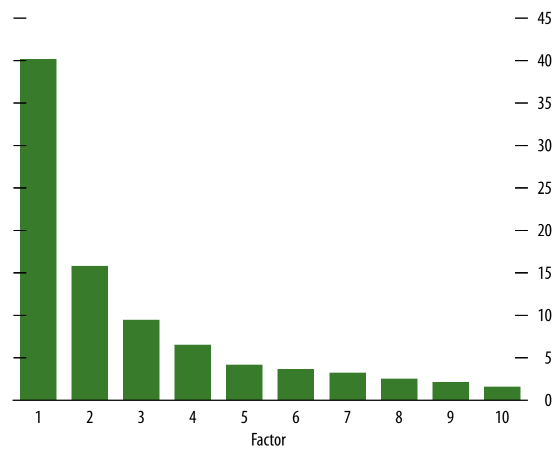
Another important policy goal is to improve the data that are integral to the proper assessment of liquidity risk. The limitations encountered in this analysis by relying only on publicly available data suggest that more disclosure of detailed information is needed to better assess the strength of the liability structure of banks' balance sheets to withstand shocks and their use of various liquidity risk management techniques. Richer data would help investors and counterparties evaluate the liquidity management practices at individual institutions. General information about the use of funding markets and institutions' own liquidity buffers would also help supervisors assess the probability that liquidity strains are building up; together with restricted information about intra-institution exposures, the information would help reveal the possible impairment of various funding markets. With more detailed public and private information, official liquidity support would likely be better targeted and more effectively provided. A first step to addressing significant data gaps is being achieved at the national and international levels through the action plans articulated in two reports prepared by the IMF and Financial Stability Board (FSB) Secretariat and endorsed by the G-20 Ministers of Finance and Central Bank Governors (the so-called G-20 Data Gaps Initiative).[23] In this context, work on developing measures of aggregate leverage and maturity mismatches in the financial system is expected to be completed in time for a June 2011 G-20 Data Gaps report.

Annex 2.1. Methods Used to Compute a Systemic Liquidity Risk Index[24]

The computation of the SLRI follows a traditional principal components analysis (PCA). Daily data were collected on 36 violations of arbitrage covering the CIP, the corporate CDS-bond basis, the swap spread, and the on-the-run versus off-the-run spread between 2004 and 2010. These arbitrage relationships involve securities traded in the euro area, Japan, South Korea, Singapore, Switzerland, the United Kingdom, and the United States. Figure 2.11 shows the first 10 factors resulting from the PCA, ordered according to their ability to account for the variation of the violations of arbitrage data in the sample. Clearly, the first principal component captures the bulk of the common variation across the 36 time series. This dominant factor is interpreted as an indicator of systemic liquidity risk in global capital markets.

A potential limitation of the SLRI is its lack of explicit treatment of the counterparty risk that underpins the ability of some traders to borrow to execute the arbitrage strategies. It is difficult to control for the effects of counterparty risk, since essentially all market-based measures of liquidity contain solvency risk, and measures of solvency risk are also affected by (market) liquidity conditions. In an attempt to explicitly mitigate the role of counterparty risk, the SLRI was regressed against the average CDS spread comprised of the 53 banks in the sample used below to analyze the relationship of the SLRI to bank performance. The residuals of the regression were taken as a new indicator of systemic liquidity conditions (NewSLRI). This

Figure 2.11. Principal Component Analysis: Total Variation Explained by Each Factor
(In percent)



Sources: Bloomberg L.P.; Datastream; and IMF staff estimates.

[23]IMF/FSB (2009, 2010).

[24]This annex was prepared by Tiago Severo and draws on Severo (forthcoming).

approach likely overestimates the role of bank-related counterparty risk in the violations of arbitrage, since the average CDS spread for banks also reflects the impact of global liquidity conditions on the banking sector. This is confirmed by regressions in which the coefficient on the SLRI is statistically significant, indicating that it explains much of the variation of bank CDS spreads over time.

The two liquidity indicators are similar in many respects. They are both very stable until early 2008 and become more volatile around the time of the March 2008 Bear Stearns collapse. After the September 2008 Lehman bankruptcy, both indexes decrease sharply, reflecting shortages in liquidity. The SLRI and the NewSLRI become less connected with each other starting in early 2009. Unfortunately, it is hard to claim that one index is superior to the other because, in practice, one cannot disentangle the true counterparty risk embedded in the SLRI.

The link between the SLRI and bank performance is analyzed with those caveats in mind. A simple model of bank returns is estimated with data on the daily equity returns of 53 global banks in Australia, Denmark, the euro area, India, Japan, New Zealand, Norway, Sweden, Switzerland, South Korea, the United Kingdom, and the United States:

$$R^i(t) = \beta_0^i + \beta_M^i \times R_M(t) + \beta_L^i \times L(t) + e^i(t). \qquad (1)$$

$R^i(t)$ is the daily dollar log-return on bank i, β_0^i is a constant, $R_M(t)$ the daily dollar log-return on the MSCI, a global index of stock returns, and represents the market factor. $L(t)$ is the daily SLRI and $e^i(t)$ is the residual. β_M^i represents a bank's exposure to equity market risk, whereas β_L^i captures its exposure to systemic liquidity risk. The estimated β_L^i are not statistically significant for all but a few of the U.S. banks. Even for those banks, the estimates are not robust once one controls for heteroskedasticity and autocorrelation of the residuals through a generalized autoregressive conditional heteroscedasticity (GARCH) model.

Interestingly, the impact of liquidity on returns is much stronger once the regressions are conditioned on the overall returns of the banking sector. More specifically, a portfolio return for the banking sector is constructed on the basis of the weighted returns for all banks in the sample, with market capitalization as the weight. Then, equation (1) is re-estimated using observations for the X percent worst days of this banking portfolio, where X is set to 25.[25] Conditional on the banking sector being in distress, bank returns seem to be strongly negatively affected by liquidity conditions. This effect is much more pronounced for U.S. and U.K. banks, whereas it is unimportant for Japanese banks. Banks in Australia, Europe, India, and South Korea lay in the middle of the distribution.

Importantly, many of the conditional estimates discussed above are not robust if the NewSLRI is substituted for the SLRI or if bank-specific information is included in the regressions. For instance, if data on each bank's CDS spread is added as a control for solvency risk in equation (1), the estimated β_L^i become insignificant for many banks. However, this approach likely underestimates the importance of systemic liquidity, since the bank-specific CDS spread is, again, also contaminated by aggregate liquidity conditions. Because it contains information about idiosyncratic shocks affecting banks as well, the ordinary least squares technique tends to attribute more weight to this variable in the regression relative to the systemic liquidity index.

That the conditional regressions based on low banking returns better explain the links between the SLRI and the level of returns means that the true link between bank equity and systemic liquidity might reside in higher moments of the return distribution (the variance of returns, for example). To study this possibility, a model of heteroscedastic stock returns is estimated in which the volatility of bank equity is a function of the SLRI and ARCH terms. More specifically, it is assumed that:

$$R^i(t) = \beta_0^i + \beta_M^i \times R_M(t) + \beta_L^i \times L(t) + \beta_X^i \times X(t) + e^i(t)\sigma(t) \qquad (2)$$

$$\sigma^2(t) = \exp(\omega_0^i + \omega_L^i L(t) + \omega_Y^i \times Y(t)) + \gamma^i e^{i2}(t-1), \qquad (3)$$

where the errors are distributed according to a normal distribution with a mean of 0 and a variance of 1,

$$e^i \sim N(0,1).$$

[25]Results are similar for values of X percent = 30 percent or X percent = 20 percent, for example.

The variables $R^i(t)$,$R_M(t)$, $L(t)$ are defined as before. X and Y represent additional controls included in the model—for example, the log of the VIX, the LIBOR-overnight index swap (OIS) spread, bank-specific CDS spreads, and so on. Parameters $[\beta_0^i, \beta_M^i, \beta_L^i, \omega_0^i, \omega_L^i, \gamma^i]$ are estimated by maximum likelihood. The choice of the exponential functional form for the conditional heteroskedasticity was made to avoid negative fitted values for the volatility process and to facilitate convergence of the estimation algorithm.

The estimated ω_L^i are strongly negative for virtually all banks in the sample. This suggests that decreases in the SLRI are associated with increases in the volatility of bank stocks, that is, banks become riskier as liquidity dries up. Such an intuitive result is robust to the inclusion of several controls in X and Y. In particular, it holds true even after including data on bank-specific CDS spreads both in equations (2) and (3). Moreover, the results are robust to the substitution of NewSLRI for SLRI, which likely understates the importance of systemic liquidity risk, as discussed above.

Liquidity Surcharge Calculation

Using the volatility model above, one can compute a liquidity surcharge designed to assess banks on the basis of their contribution to the externality associated with their excessive exposure to systemic liquidity risk. The technique relies on the contingent claims analysis (CCA) approach, in which public authorities are assumed to provide an implicit guarantee for bank liabilities. The guarantee is modeled as an implicit put option on the assets of the bank, with strike price and maturity determined by the characteristics of bank debt. The estimated ω_L^i allows regulators to calculate the degree to which each bank's implicit put value changes as the volatility of equity increases because of liquidity stress.

More specifically, on the basis of option pricing formulas, the unconditional volatility of the market value of a bank's assets can be recovered using data on the characteristics of its liabilities and the observed unconditional volatility of the bank's equity. This information is sufficient to calculate the unconditional price of the implicit put granted to banks by public authorities. An identical calculation is performed using the estimated volatility of equity conditioned on a liquidity stress period, say when the SLRI is 2 or 3 standard deviations below its mean, but keeping other factors constant. This yields the value of the put conditioned on a systemic liquidity stress period. The difference between the prices of the conditional and the unconditional puts represents the increase in the value of contingent liabilities due to liquidity shortages.

Banks can thus be charged by the public authorities according to their individual contribution to these conditional liabilities, making them, in essence, prepay the costs of relying on public support during periods of systemic liquidity distress. Of course, the details underpinning the put values (both unconditional and conditional) would need to be decided, but interestingly, this hypothetical surcharge would not be contaminated by idiosyncratic liquidity risk, since the SLRI is systemic in nature. Moreover, to the extent that the bank-specific CDS spreads are included in equations (2) and (3), neither would the liquidity surcharge be directly affected by solvency risk. This feature helps to address concerns about the overlap between capital and liquidity regulation.

Annex 2.2. Technical Description of the Systemic Risk-Adjusted Liquidity Model[26]

The proposed systemic risk-adjusted liquidity (SRL) model combines market prices and individual firms' balance sheet data to compute a risk-adjusted measure of systemic liquidity risk. That measure links a firm's maturity mismatch between assets and liabilities and the stability of its funding with those characteristics at other firms that are subject to common changes in market conditions.

The methodology follows three steps (Figure 2.12):

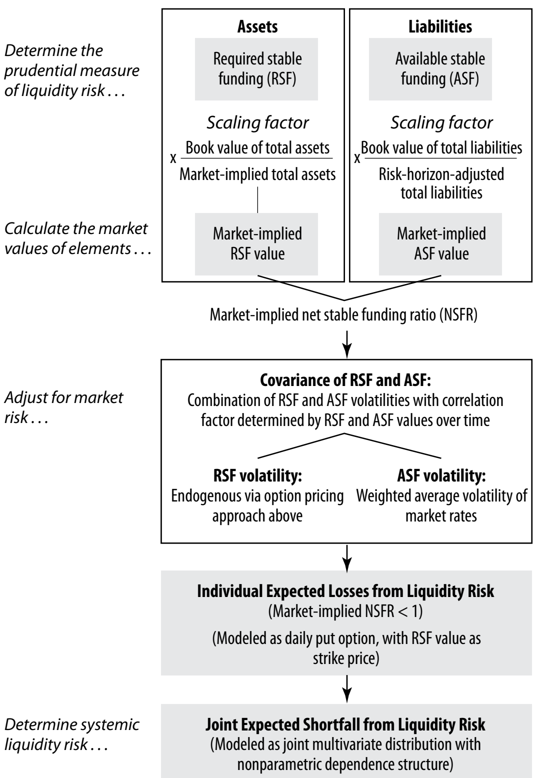
Step 1: Derive a daily measure of the NSFR at market prices, where the required stable funding (RSF) and available stable funding (ASF) values reflect differences between the balance sheet and actual market values of total assets to liabilities of each firm. The actual balance sheet measures of ASF and RSF values are re-scaled by the ratio of the book value of total assets to implied assets (which are obtained as a risk-neutral density from equity option prices with maturities

[26]This annex was prepared by Andreas Jobst and draws on Jobst (forthcoming).

between 3 and 12 months), and by the ratio of the book value of total liabilities to the present value of total liabilities, respectively.[27]

Step 2: Determine the expected losses from liquidity risk using an adapted version of CCA.[28] The market-implied expected loss associated with the liquidity position defined by the revised NSFR measure (obtained in step 1) can be modeled as an implicit put option in which the present value of RSF represents the "strike price," with the short-term volatility of all assets underpinning RSF determined by the implied volatility derived from equity options prices.[29] More specifically, the option value is determined on the basis of the assumption that the value of the ASF follows a random walk with intermittent jumps that create sudden and large changes in the valuation of the liabilities (which is modeled as a Poisson jump-diffusion process). The volatility of these liabilities included in the ASF is computed as a weighted average of the observed volatilities of latent factors derived from a set of market funding rates deemed relevant for banks, as identified by a dynamic factor model. [30] These two

Figure 2.12. Methodology to Compute Systemic Liquidity under the Systemic Risk-Adjusted Liquidity Model



[27]Estimations of these scaling factors, and the subsequent covariance and the joint expected losses, are computed over a rolling window of 120 working days to reflect their changing characteristics.

[28]The CCA is a generalization of option pricing theory pioneered by Black and Scholes (1973) and Merton (1973). It is based on three principles that are applied in this chapter: (1) the values of liabilities are derived from assets; (2) assets follow a stochastic process; and (3) liabilities have different priorities (senior and junior claims). Equity can be modeled as an implicit call option, while risky debt can be modeled as the default-free value of debt less an implicit put option that captures expected losses. In the SRL model, the Gram-Charlier extension combined with a jump-diffusion process is applied to account for biases in the Black-Scholes-Merton specification (Backus, Foresi, and Wu, 2004; Bakshi, Cao, and Chen, 1997).

[29]The NSFR reflect the impact of funding shocks as an exposure to changes in market prices in times of stress. The procedure can be applied to other measures of an individual firm's liquidity risk.

[30]A dynamic factor model of the ASF is specified based on one principal component extracted from each group of maturities of observed market rates: short-term sovereign rate (with maturities ranging from three to twelve months); long-term sovereign rates (with maturity ranging from three to ten years); total equity market returns (domestic market and Morgan Stanley Composite Index); financial bond rates (investment grade, both medium- and long-term); domestic currency LIBOR (ranging from three to twelve months); and the domestic short-term currency OIS as

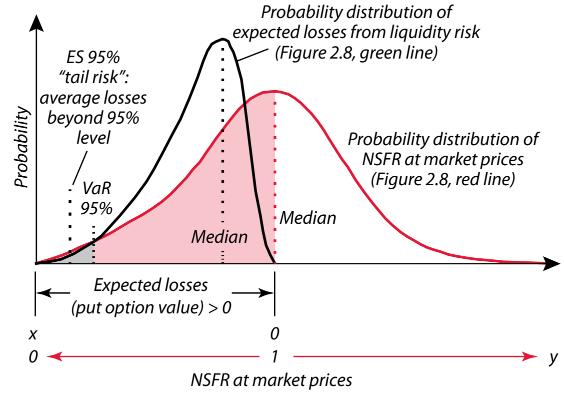
time-varying elements provide the basis for computing a put option, which has intrinsic value (is in-the-money) when the market value of the ASF falls below that of the RSF, constituting an expected loss due to liquidity shortfall. The value of this derived put option can be shown to result in significant hypothetical cash losses for an individual firm as the risk-adjusted NSFR declines.

Figure 2.13 illustrates the relation between these expected losses (step 2) and the NSFR at market prices (step 1) as distribution functions (based on multiple observations of each over a certain period of time). Expected losses arise once there is some probability that the NSFR drops below the regulatory requirement to be greater than 1. The greater the potential funding distress projected by a declining NSFR, the greater are these losses. The tail risk of an individual expected liquidity shortfall is represented by the expected shortfall (ES) at the 95th percentile, which is the area under the curve beyond the value-at-risk (VaR) threshold value.

Step 3: Derive systemic (aggregate) expected losses for all sample firms. Use the probability distribution of expected losses arising from an individual firm's implied NSFR (obtained in step 2) to calculate a joint probability of all firms experiencing a liquidity shortfall simultaneously (step 3). One combines the marginal distributions of these individual expected losses with their nonlinear dependence structure (estimated via a nonparametric copula function) to determine an extreme value multivariate distribution by following the aggregation mechanism proposed under the systemic CCA framework (Gray, Jobst, and Malone, 2010; Gray and Jobst, 2010; Gray and Jobst, forthcoming; and Jobst, forthcoming). Using this multivariate distribution, one can use estimates of the joint tail risk, such as the ES at a statistical confidence level of 95 percent or higher, to gauge systemic liquidity risks. One can also extract the time-varying contribution of each individual firm to the joint distribution (by calculating the cross-partial derivative) and use this amount to develop a capital surcharge or a fair value risk premium for systemic liquidity risk.

explanatory variables. The volatility of ASF is calculated as the average volatility of these market rates weighted by the regression coefficient of each principal component.

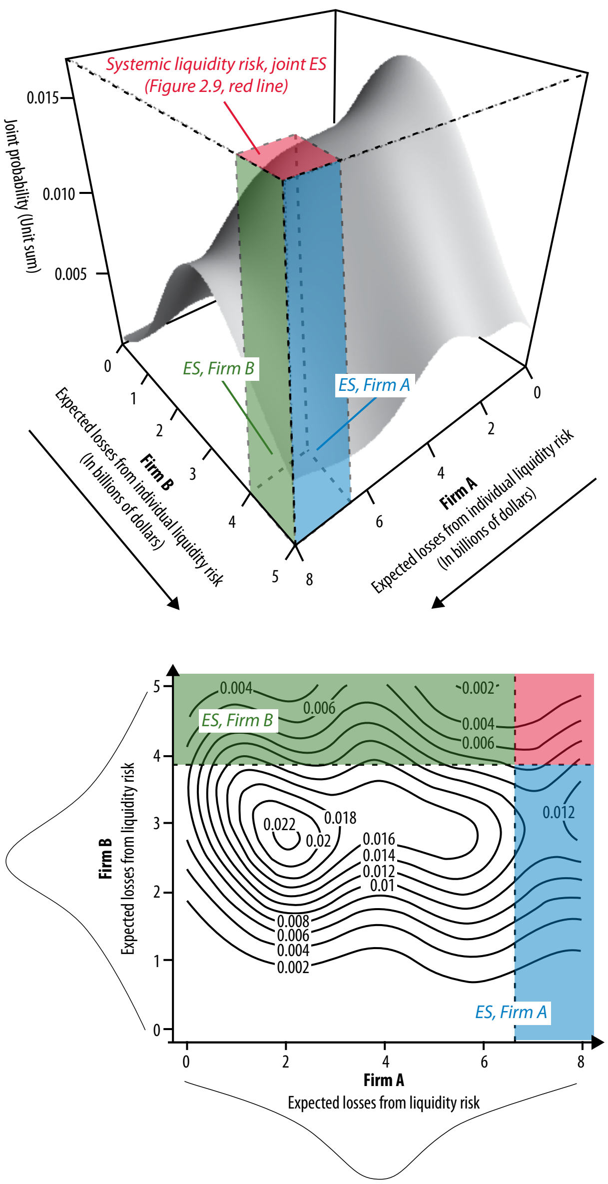
Figure 2.13. Conceptual Relation between the Net Stable Funding Ratio at Market Prices and Expected Losses from Liquidity Risk



Source: IMF staff estimates.
Note: Expected losses are modeled as a put option. NSFR = net stable funding ratio; VaR = value at risk; ES = expected shortfall.

Figure 2.14. Conceptual Scheme for the Probability Distribution of Joint Expected Shortfall from Liquidity Risk: Two-Firm (Bivariate) Case

(In percent)



Sources: IMF staff estimates.

Note: Expected losses are modeled as a put option.

ES= expected shortfall. ES shown at 95 percent confidence level.

Figure 2.14 illustrates the bivariate case of expected losses determining the joint probability of two sample firms experiencing a liquidity shortfall at the same time, using the estimation results from step 3. The top panel of Figure 2.14 shows the density function of two firms (Bank A and Bank B). The probability of systemic liquidity risk is captured by combining the individual bank estimates (depicted by the green and blue panels), which generates the joint expected shortfall at the 95th percentile (red cube). The top panel can also be shown in two-dimensions as a so-called contour plot (see bottom panel of Figure 2.14.).

Capital Surcharge and Insurance Premium Calculations

In particular, the above measure of systemic liquidity risk, if applied to a banking system, can be used to calibrate two price-based measures, a capital surcharge and an insurance premium, either of which could be used as a macroprudential tool to help mitigate systemic liquidity risk. Implicitly, these two measures proxy for the amount of contingent support that banks would receive from a central bank in times of systemic liquidity stress.

- A capital surcharge could be based on a firm's own liquidity risk (highest risk-based NSFR over some pre-specified period, such as one quarter) or its marginal contribution to joint liquidity risk, whichever is higher.
- An insurance premium could be based on an actuarial fee imposed on firms, which would be used to compensate them for expected losses in a systemic event when they fall below the minimum required NSFR of 1 in concert with other banks.

Numerical examples of these two approaches are in the main text of the chapter, and their calculations are explained below.

For the capital surcharge, the method follows the current bank supervisory guidelines for market risk capital requirements (BCBS, 2009), in which the VaR is calculated each day and compared to three times the average quarterly VaRs over the last four quarters. The maximum of these two numbers becomes the required amount of regulatory capital for market risk. In a similar way, each firm j would need to meet an additional capital requirement, c_{SLR}

(in dollars), at time t, to offset its contribution to systemic liquidity risk at a statistical confidence level of $a = 0.95$. First, choose the higher of (1) the previous quarter's expected shortfall $ES(a)_{j,t-1,\tau}$ at percentile a associated with *individual* expected losses and (2) the average of this quarterly measure over the preceding four quarters, multiplied by an individual multiplication factor κ_j. This amount would be compared to the last available average quarterly *marginal contribution*, $\overline{MC(a)}_{j,t-1,\tau}$, measured as a probability multiplied by the systemwide $ES(a)_{t-1,\tau}$, in dollars, and the average of this quarterly measure over the preceding four quarters, multiplied by a multiplication factor κ. The higher of the two maximums would then be the surcharge. Therefore, based on an estimation window of τ days for ES, the capital surcharge c_{SLR} would be

$$c_{SLR} = \max \left\{ \begin{array}{l} \max \left\{ ES(a)_{j,t-1,\tau};\ \kappa_j \times \frac{1}{4}\sum_{t=-4}^{0} ES(a)_{j,t,\tau} \right\}; \\ \max \left\{ \overline{MC(a)}_{j,t-1,\tau} \times ES(a)_{t-1,\tau}; \right. \\ \left. \qquad \kappa \times \frac{1}{4}\sum_{t=-4}^{0} \left(\overline{MC(a)}_{j,t,\tau} \times ES(a)_{t,\tau} \right) \right\} \end{array} \right\}$$

The comparison of the two maximums is motivated by Figure 2.9, whereby an individual firm's liquidity risk (its own expected loss) may be higher than its systemic risk contribution, which underscores the importance of analyzing the interlinkages between firms and how they influence the realization of joint tail risks. Note that the amount of capital to be withheld is exactly the (probabilistic) amount needed to offset the losses that would be incurred for a given level of statistical confidence when the NSFR > 1 requirement is violated.

An alternative method is to require firms to pay a systemic liquidity insurance premium that would amount to a prepayment for liquidity support based on the likelihood of a systemwide liquidity shortfall. The individual contribution to systemic liquidity risk can be used to calculate a fair value price for insurance specific to each firm. To illustrate this, the average marginal contribution of each firm to systemwide expected shortfall (with statistical probability a) is first divided by the average of the discounted present value of RSF over the previous four quarters. This is the ratio of the potential systemically based dollar losses of firm j to its required stable funding—the probabilistic proportion of underfunding (if greater than 1) in times of stress, akin to a probability of distress for a certain risk horizon. Assuming that this probability is constant over time and can be expressed as an exponential function over time, the fair value of a risk-based insurance premium can be obtained as the natural logarithm of 1 minus the above ratio and multiplied by the negative inverse of the time period under consideration. Unlike the capital surcharge, which is meant to absorb losses at any point in time, the insurance premium is measured over time (in this case, one year ahead) and thus spreads out the probability of the firm's experiencing a liquidity shortfall over a risk horizon and as a result will appear as a lower cost.

More specifically, the cost f_{SLR} of insuring stable funding over the short term against possible liability run-offs can be calculated by multiplying the estimated conditional insurance premium with the value of average uncovered short-term liabilities $L^{ST}_{j,t}$ (i.e., excluding secured deposits) over the previous four quarters as a nominal base. This amount would compensate for the individual firm's cost of future systemic liquidity support. Thus, firm j's premium would be,

$$f_{SLR} = -\frac{1}{T} \ln \left(1 - \frac{\sum_{t=-4}^{0} \left(\overline{MC(a)}_{j,t,\tau} \times ES(a)_{t,\tau} \right)}{\sum_{t=-4}^{0} \overline{RSF}_{j,t} \times \exp(-r(T-t))} \right) \times \frac{1}{4}\sum_{t=-4}^{0} \overline{L}^{ST}_{j,t}$$

where r is the risk-free rate and $T-t$ (that is, residual maturity) is the time horizon.[31]

Because they take into account a single firm's time varying contribution to systemic liquidity risk, either the capital surcharge or the insurance premium could be used as price-based macroprudential tool to instill incentives for more resilient and diversified funding structures. Based on estimates during times of stress, both measures could be refined to avoid procyclical tendencies. For instance, in the context of the capital surcharge, the multiplication factor κ_j could be calibrated on data obtained during times of stress and set

[31]Note that this approach could also be used to identify the effectiveness of closer supervisory monitoring in response to identified liquidity problems of a particular bank. That can be done if remedial actions decrease the bank's contribution to overall systemic risk from liquidity shortfalls up to the point where it closely matches the individual liquidity risk.

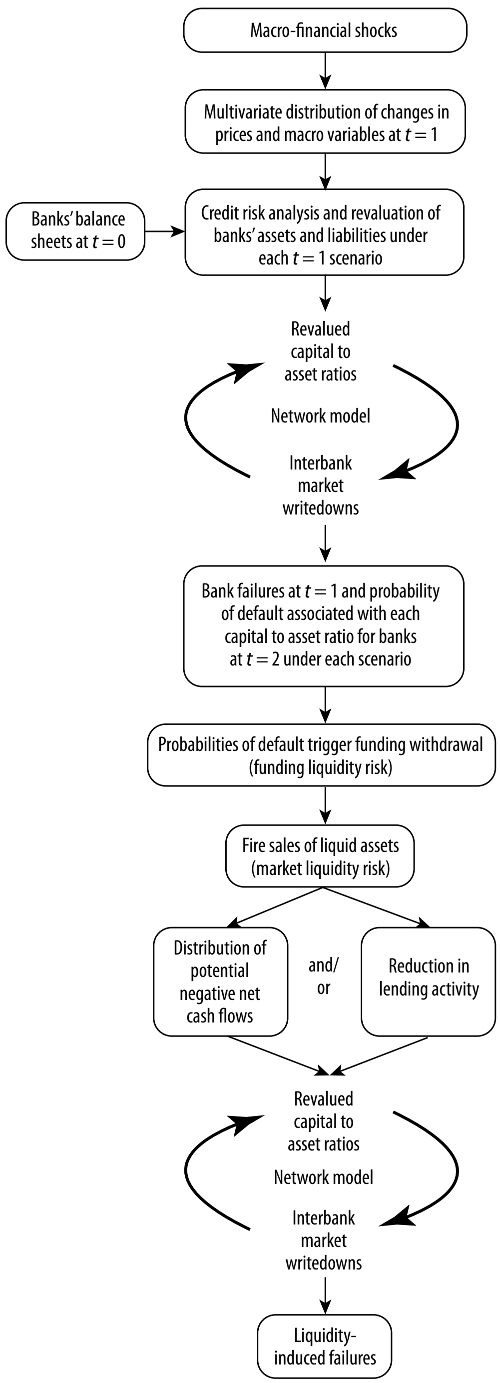
such that minimum prudential levels of capital charges are maintained.

Annex 2.3. Highlights of the Stress-Testing Framework[32]

The stress-test (ST) approach takes as a starting point the view that systemic liquidity runs are extreme episodes of market-imposed discipline stemming from concerns about the value of bank assets—in the latest crisis, from depressed values for subprime mortgages and structured products affected by the fall in house prices (see Afonso, Kovner, and Schoar, 2010).

The ST approach is applied to 10 stylized U.S. banks calibrated with Call Report data: two small local banks with assets concentrated in California and Florida-Georgia respectively; three middle-sized regional banks (east coast, midwest, and west coast); three large banks; and two megabanks. The Call Report is the term used for the data collected quarterly by the Federal Financial Institutions Examination Council from most insured banks in the United States. The megabanks account for just over 60 percent of banking assets in this stylized sample. The approach proceeds in four stages: (1) modeling of the financial and economic environment; (2) credit risk modeling; (3) systemic solvency risk modeling; and (4) systemic liquidity risk modeling (Figure 2.15).

Figure 2.15. Systemic Liquidity Risk ST Framework



Financial and Economic Environment Modeling

A forward-looking simulation methodology is applied to the 10 banks simultaneously for modeling correlated systemic solvency and liquidity risks. One element that makes the model systemic is that all entities (individuals, financial and nonfinancial institutions, regulators, governments, and so on) will experience the same financial and economic environment. Financial and economic shocks can be expected to produce correlated solvency and liquidity risks for banks, some of which have similar asset and liability structures.

[32]This annex was prepared by Theodore Barnhill Jr. and Liliana Schumacher and draws on Barnhill and Schumacher (forthcoming).

The simulation of the financial and economic environment requires the specification of trends, volatilities, and correlations of a number of important financial and economic variables. From this set of variables and their statistical attributes, thousands of potential future financial environments are created over a selected time-step (for example, T1 is one year). A "bad" regime can be chosen to demonstrate a higher risk of an adverse period. In this application, the variables in the financial and economic environment include domestic and foreign interest rates, interest rate spreads, foreign exchange rates, U.S. economic indicators, global equity indices, equity returns from 14 S&P sectors, and real estate returns from 20 Case-Shiller regions. The adverse period 2007–2010:Q1, with low equity returns and negative regional real estate returns, is used to generate the stress test results.

Credit Risk Modeling[33]

Bank solvency and liquidity risks are driven by bank asset and liability structures, loan credit quality, sector and regional loan concentrations, and equity capital levels. In this application, the 10 stylized banks are constructed to be representative of the U.S. banking system, with various sizes, asset and liability structures, and equity capital ratios taken from aggregated, publicly available data. A larger or smaller number of banks could be modeled.

Changes in the ratio of equity capital to assets, and hence solvency risks, are outputs of a standard credit risk model. For instance, assessments of business and mortgage credit risk are based on simulations, respectively, of business debt-to-value ratios and property loan-to-value ratios using a Merton-type model.[34] Recovery rates on business loans are systematically related to stock market returns, and those for mortgage loans are assumed to be the property loan-to-value ratio less a 30 percent liquidation cost.[35] Correlated market risk for approximately 100 other bank assets and liabilities is also modeled. These analyses produce correlated capital ratios and solvency risk assessments (probabilities of default) for all 10 banks in each run of the simulation at the selected time step, which allows systemic risk assessments to be undertaken.

Systemic Solvency Risk Modeling

The outcomes of the risk assessments of the financial and economic environment and bank portfolios after many simulation runs are joint distributions of each of the 10 bank's ratio of equity capital to assets and other balance sheet information at the selected time step. This information is used to estimate the banks' correlated default probabilities and systemic banking system risks.

During times of economic stress, it is likely that default losses on loans will increase, and many banks will either fail or be weakened significantly, particularly if they have similar asset and liability structures. This is just the time when the failure of several banks could, through interbank credit defaults, precipitate a number of simultaneous bank failures.

The interbank credit risk is modeled using a network methodology. In the current study, and consistent with current U.S. regulations, a bank fails when its ratio of equity capital to assets falls below 2 percent.[36] In this case, the bank becomes incapable of honoring its interbank obligations and defaults on them.[37] The recovery rate on these interbank obligations is set at 40 percent, and this would affect other banks' capital ratios and potentially lead to additional bank failures. The network methodology is applied repeatedly until no additional banks fail, after which the probability of multiple simultaneous bank failures (that is, systemic solvency risk) can be computed.

[33]The risk assessments reported in this analysis were undertaken with the ValueCalc Banking System Risk Modeling Software, copyright FinSoft, Inc. The IMF does not endorse the use of this, or any other, software.

[34]For a more detailed discussion, see Barnhill and Maxwell (2002).

[35]See Varma and Cantor (2005). For more information see Barnhill, Papapanagiotou, and Schumacher (2002).

[36]The Prompt Corrective Action provision in the FDIC Improvement Act of 1991 states that a bank should be closed when its tangible capitalization reaches 2 percent. The trigger point for bank failure could be set in the ST framework model at any relevant regulatory level, including the new leverage ratio as proposed under Basel III.

[37]In the current study precise information on inter-bank borrowers' and lenders' identities is unavailable; hence the amount of interbank loans made between each bank is assumed to be proportional to their total inter-bank borrowing and lending.

Modeling Correlated Systemic Liquidity Risk

The model's primary contribution to stress testing is the addition of correlated liquidity runs on banks, driven by heightened risks, or uncertainties, regarding future bank solvency. When multiple banks fail, it is highly likely that the risk of future insolvency for the remaining banks is elevated. At the end of each run of the time step simulation (for example, at T1), future (T2) solvency risks for each bank are computed. When a bank's probability of default at T2 is 10 percent (or 20 percent, or 40 percent), it is assumed that it results in a liquidity run that reduces that bank's total liabilities by 5 percent (or 10 percent, or 25 percent, respectively).[38]

Banks that face a liquidity run are assumed to follow the following sequence of events. At first, banks stop lending in the interbank and repo markets, liquidate interest bearing bank deposits, sell government securities, and sell other securities. If these steps do not produce adequate liquidity, they ultimately default on their obligations. Second, the banks sell their liquid securities and reduce their loan portfolios in proportions similar to that observed in U.S. bank holding companies having elevated failure probabilities. Additional bank losses result from the sale of assets at fire sale prices.

It is possible to estimate the distribution of potential banking system loan reductions resulting from systemic liquidity events. In severe cases, such reduced bank lending may lead to a credit shortage with substantial adverse impacts on the real economy.

Both liquidity failures of counterparty banks and the fire sale of assets may produce further losses for banks that adversely affect their solvency. Again, these can be modeled with a network methodology applied repeatedly until no additional banks fail. In this way the probability of multiple simultaneous bank failures (that is, correlated systemic solvency and liquidity risk) can be assessed.

Correlated systemic solvency and liquidity risks may be reduced by moderating the volatility in the financial and economic environment or by altering banks' asset and liability structures, loan credit quality, sector and regional loan concentrations, and equity capital levels. The model can assess the systemic impact of changes in any combination of these variables.

[38]These assumptions are based on the analysis of changes in total liabilities for a group of about 700 insured bank holding companies relative to their estimated probability of default. System-wide weighted average default probabilities are modeled and it is assumed that they have some impact on the market's assessment of future bank default probabilities and liquidity runs.

Data Requirements

The ST approach, which is quite data intensive, has the following data requirements. In some cases, it may be possible to substitute expert opinion for data that may not be available.

- Time series related to the financial and economic environment in which banks operate. These series need to be of sufficient length to allow trends, volatilities, and correlations to be estimated during both "normal" and "stress" periods. The following data are of interest:
    - short-term domestic and foreign interest rates and their term structures
    - interest rate spreads for loans of various credit qualities (securities)
    - foreign exchange rates (as relevant)
    - economic indicators (gross domestic product (GDP), consumer price index, unemployment, and so on)
    - commodity prices (oil, gold, and so on)
    - sector equity indices
    - real estate prices
- Information on banks' assets, liabilities, and, ideally, off-balance-sheet transactions, including hedges, such as:
    - various categories of loans, including information about their credit quality, maturity structure, and currencies of denomination
    - currency and maturity structure of the other assets and liabilities
    - capital as well as operating expenses and tax rates
    - clients' leverage ratios and recovery rates, to be able to calibrate credit risk models
    - interbank exposures, including bilateral credit exposures among the various banks
- Information to enable calibration of behavioral relationships, such as:

- between banks' default probabilities and funding reduction due to bank creditors' concerns about solvency
- between asset fire sales and asset values (including haircuts), which in turn affect liquidity and solvency ratios

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